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DO ANALYSTS ANCHOR THEIR RECOMMENDATION REVISIONS TO VALUATION MULTIPLES?

Master's Thesis
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Abstract of master's thesis

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Purpose of the study

The key objective is to study whether analysts partly anchor their recommendation revisions to the 52-week high and low stock prices as well as to the median forward-looking consensus valuation multiples, particularly to the 2-year high and low P/E ratios. The potential anchoring effects of valuation multiples have previously been left without academic attention even though analysts often justify their recommendation revisions by stating P/E and PEG ratios, indicating that they may use these valuation multiples to reach their recommendation decisions. As recommendations are forward-looking predictions, uncertainty and intuition are involved making analysts prone to use simple heuristics not only to communicate with investors but also to revise their recommendations.

Data and methodology

My sample consists of 35,270 analyst recommendation revisions from 5,193 analysts for 1,454 unique US stock-listed companies. The dataset covers time period from November 1993 to September 2015. Analyst stock recommendations and earnings estimates data were gathered from IBES database, stock exchange data from CRSP database, accounting data from Compustat database, institutional ownership of stocks from Thomson Reuters and idiosyncratic volatility from Kenneth R. French's database. To study the effects of reference points on recommendation downgrades, I employ a series of conditional fixed effects logistic regression models by controlling price and earnings momentum effects, valuation, fundamental and growth indicators as well as company and analyst specific factors related to analyst stock recommendation decisions.

Findings

Partly consistent with prior literature, I find that analysts tend to downgrade recommendations near the 52-week high and 52-week low stock prices. Furthermore, from the most common relative valuation multiples used by analysts, only P/E ratio and PEG ratio show some statistically significant evidence of anchoring to valuation multiples. With all control variables included, the odds of being downgraded by analysts are over 40% higher for companies approaching the 52-week high or low than that for other companies. In the case of approaching the 2-year high and 2-year low P/E ratios, the odds of being downgraded by analysts are 15% and 20% higher, respectively, although the evidence on the statistical significance is mixed. Provided evidence suggests that the 52-week high and low stock prices are more important reference points for analysts than high and low points of valuation multiples. Despite these anchors, my main results suggest that two other factors create by far the largest effects on revisions: price momentum in the recent weeks increases the odds and a high number of earnings forecast revisions decreases the odds of downgrading the most.

Keywords analyst, recommendation, multiples, 52-week high and low stock price, P/E ratio

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Tutkimuksen tarkoitus

Tutkimuksen tarkoituksena on tutkia, vaikuttavatko osakesuositusta edeltävän 52 viikon ylin tai alin osakkeen hinta tai yleisimmin käytetyt arvostuskertoimet analyytikoiden päätöksentekoon ja heidän antamiinsa osakesuosituksiin. Analyytikoiden ankkuroitumista arvostuskertoimiin ei ole tutkittu aikaisemmin, vaikka analyytikot perustelevatkin usein suositusten muutoksiaan sijoittajille käyttäen yleisiä arvostuskertoimia, erityisesti P/E- ja PEG-suhdelukuja. Tämä viittaa siihen, että analyytikot käyttävät arvostuskertoimia päätöksenteossaan eivätkä pelkästään viestiäkseen yksinkertaisella tavalla suositusten muutoksista sijoittajille. Analyytikot altistuvat yksinkertaisille ja heuristisille päätöksentekomenetelmille myös siksi, että osakesuositukset ennustavat tulevaa kurssikehitystä ja sisältävät siten aina epävarmuutta ja analyytikon omaa intuitiota.

Lähdeaineisto ja tutkimusmenetelmät

Tutkimuksen aineisto koostuu 5 193 analyytikon 35 270 osakesuosituksen muutoksesta 1 454 yhdysvaltaiseen pörssiyritykseen. Suositukset on annettu vuosina 1993-2015. Analyytikoiden suositukset ja ennusteet on kerätty IBES-aineistosta, pörssikurssi-informaatio CRSP-aineistosta, tilinpäätösaineisto Compustatista, institutionaalisten sijoittajien omistukset Thomson Reutersista ja osakkeen idiosynkraattinen volatiliteetti Kenneth R. Frenchin ylläpitämästä aineistosta. Suosituksen muutoksiin vaikuttavia tekijöitä on tutkittu käyttäen ehdollista kiinteät vaikutukset huomioon ottavaa logistista regressiota. Regressioita on mallinnettu ottaen huomioon viimeaikaiseen osakkeen hinnan kehitykseen ja tuloskehitykseen perustuvia muuttujia, yrityksen arvostukseen, tunnuslukuihin ja kasvuun perustuvia muuttujia sekä muita yritys- ja analyytikkokohtaisia muuttujia, joilla on empiirisesti havaittu vaikutusta osakesuosituksiin.

Tulokset

Empiiristen tulosten perusteella analyytikot laskevat suosituksiaan, kun osakekurssi lähestyy edeltävän 52 viikon ylintä tai alinta osakekurssia. Odds ratio -kerroin on yli 40% korkeampi yrityksille, joiden osakkeen hinta lähestyy edeltävän 52 viikon ylintä tai alinta hintaa. Tulokset eivät tue yhtä vahvasti ankkuroitumista yleisimmin käytettyihin arvostuskertoimiin. Vain P/E ja PEG -suhdeluvut antavat tilastollisesti merkitseviä tuloksia. Odds ratio -kertoimet ovat 15% korkeammat yrityksille, jotka lähestyvät 2 vuoden ylintä P/E-suhdelukua ja 20% korkeammat lähestyessä 2 vuoden alinta. Täten 52 viikon ylimmän ja alimman osakekurssin merkitys on suurempi kuin arvostuskertoimien merkitys. Tuloksista selviää myös, että tulosennusteiden ahkera päivittäminen korreloi vahvasti suositusten nostamisen kanssa ja että merkittävin suosituksia alentava vaikutus on sillä, että osakkeen hinta on noussut viimeisten viikkojen aikana huomattavasti.

Avainsanat analyytikko, suositus, arvostuskertoimet, 52 viikon ylin ja alin osakekurssi, P/E-luku

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1. Introduction

In the continuously changing financial markets, analysts need to make plenty of decisions and forecasts with limited amount of information and time. Decision making is not only limited by the bounded rationality[1] but future predictions almost always include an irreducible intuitive component. Tversky and Kahneman (1974) find that the general characteristics of intuitive judgments under uncertainty are the reliance on heuristics and the presence of common biases. Bias means that these errors of judgements are systematic rather than random.

Ideally, the best analysts do not fall in love with their current recommendations but are ready to revise them in the light of new information. They also avoid the opposite mistake of assuming that this changes everything. They are good at avoiding under- and overreactions. Nonetheless, there is vast evidence that behavioral biases affect analysts as well as other financial market professionals[2]. For instance, Amir and Ganzach (1998) show that anchoring and adjustment leads to underreaction in analyst forecasts while representativeness bias leads to overreaction and leniency leads to more optimistic predictions.

Tversky and Kahneman (1974) refer to anchoring when people make estimates by starting from an initial value which is then adjusted to yield the final answer. However, they find that these adjustments are usually insufficient and different starting points yield different estimates which are biased towards the initial values. In other words, the initial value carries an unreasonably high weight in the person's decision-making process. In the stock market, anchoring can mean for e.g. locking your view into a reference point such as purchase price, specific historical stock price or relative metrics such as P/E ratio.

The aim of this thesis is to shed light on the decision-making of the sell-side equity analysts, specifically whether analysts partly anchor their views on the company by using rule-of-thumb valuation multiples to revise their stock recommendations. In this thesis, the focus is on the most commonly used market multiple by analysts, price-to-earnings (P/E ratio). In addition, other commonly used market multiples are tested, specifically EV/EBITDA, EV/EBIT and EV/Sales (Pinto et al., 2015). Furthermore, anchoring on PEG ratio (price/earnings to growth) is also tested since analysts often justify their recommendations using both P/E and PEG ratios (Bradshaw, 2002). Moreover, as Li et al. (2016) find, 52-week high stock price may serve as

[1] See Simon (1955) for discussion and theory of physiological limits on human cognition.
[2] For other finance professionals see e.g. Staël Von Holstein (1972), George and Hwang (2004), Yuan (2015).

an anchor for analysts. My first hypotheses 1-2 test whether my sample confirms the results of Li et al. (2016).

1.1 Research questions and testable hypotheses

My first research question relates to the 52-week high phenomenon, specifically, are analysts more likely to downgrade the recommendation when the stock price approaches the 52-week high stock price. Furthermore, I also test whether the 52-week low phenomenon is found, specifically are analysts more likely to upgrade the recommendation when the stock price approaches the 52-week low stock price. There are many academic papers that have found significant results with 52-week low phenomenon among investors[3], and thus it is worth the study. Nevertheless, it is worth mentioning that Li et al. (2016) do not find statistically significant results for the 52-week low phenomenon.

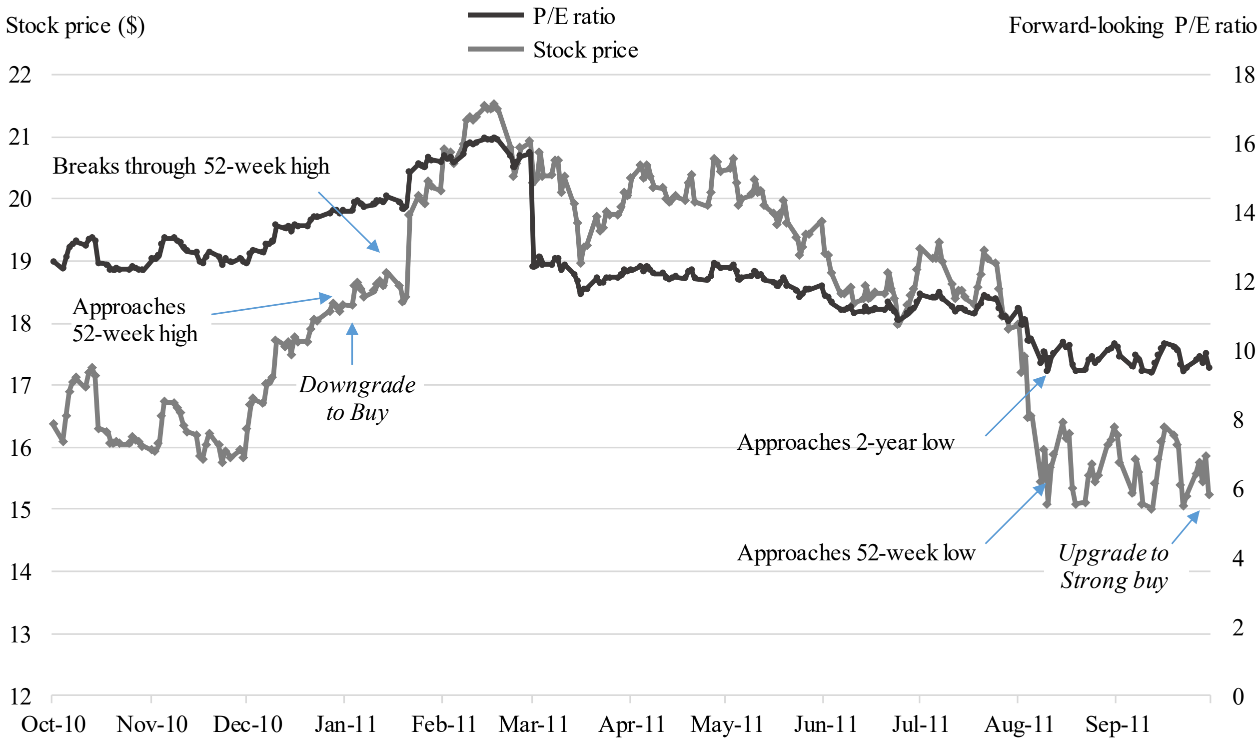
My second research question relates to price-to-earnings ratio (P/E) and its function as an anchor for analysts. Does P/E ratio serve as a reference point for analysts when they are revising their recommendations, resulting in underreaction to new information? For instance, when the P/E ratio of a stock is approaching its historical low points, some market participants often view the stock price as cheap, and analysts might believe that the stock has thus more upside potential and has become more attractive. This anchoring effect on P/E ratio might lead analysts to revise their recommendations close to these potential reference points. Similarly, when P/E ratio is approaching historical high points, the company may be perceived overvalued by analysts, resulting in analysts downgrading the stock. The effect is essentially similar to anchoring on the 52-week high or 52-week low but instead of stock price, the P/E is the main anchor.

In Figure 1, an example of potential anchoring of 52-week high/low phenomenon is illustrated. It shows that an analyst may have anchored his view to both 52-week high and 52-week low stock prices as his recommendation revisions are issued when the stock price is approaching the 52-week low and 52-week high. Analyst D. Holland downgrades his recommendation when the stock price is approaching the 52-week high and upgrades his recommendation back to previous level when it is approaching the 52-week low stock price. Moreover, the forward-looking P/E ratio is also illustrated in Figure 1 and it is noticeable that the forward-looking P/E ratio is also approaching the 2-year low P/E ratio at the same time than it is approaching the 52-week low stock price.

[3] See e.g. Brock, Laknishok, and LeBraon (1992), George and Hwang (2004) and Huddars, Lang and Yetman (2008).

Figure 1. Daily stock price and P/E ratio of General Electric and analysts' stock recommendation revisions

Figure 1 shows daily stock price and forward looking P/E ratio of General Electric and recommendation revisions during the one-year period between October 2010 and September 2011. Only one analyst revises recommendations during that period. Analyst D. Holland downgrades his recommendation from *Strong buy* (5) to *Buy* (4) in January 6, 2011 and upgrades it in September 22, 2011 from *Buy* (4) to *Strong buy* (5). In the first revision, the stock price is approaching the 52-week high stock price when the analyst downgrades the stock and in addition the stock has not yet broken through the 52-week high 'resistance level'. In the latter case, the same analyst upgrades the stock back to *Strong buy* (5) and the stock price is approaching the 52-week low stock price and the P/E ratio is also approaching the 2-year low P/E ratio. Furthermore, the stock price and the P/E ratio have not yet broken through the 52-week low stock price and 2-year low P/E 'support levels', respectively.



The anchoring effect of 52-week high and low phenomenon is similar when P/E works as an anchor. Consider the following example. An analyst upgrades his recommendation from *Buy* to *Strong buy* and justifies his recommendation stating that the median forward-looking P/E multiple has dropped close to the 2-year low. However, a few days before his recommendation revision, the company announced new information about its weakened growth prospects. The analyst may have performed complex models and extensive analyses about the company but it can as well be that the stock price has hit a 'support level' in the analyst's mind and the analyst has underreacted to the bad news provided by the company[4]. The analyst may have anchored his view to a certain, higher P/E multiple, leading him to adjust his views only partially. Thus, analyst upgrades his recommendation to *Strong buy*. Similarly, an analyst may see e.g. the 2-

[4] According to Bradshaw (2011), there is no general consensus whether analysts over- or underreact to information.

year high P/E multiple as an upper bound for the stock and as a result, the analyst downgrades the stock. In other words, the high P/E multiple works as a price barrier in the analyst's mind as he thinks that the stock price has little room to grow and is more likely to fall.

The main hypotheses are as follows:

H1: *Analysts are more likely to downgrade the recommendation when the company's stock price approaches the 52-week high stock price.*

H2: *Analysts are less likely to downgrade the recommendation when the company's stock price approaches the 52-week low stock price.*

H3: *Analysts are more likely to downgrade the recommendation when the company's price-to-earnings multiple approaches the 2-year high price-to-earnings multiple.*

H4: *Analysts are less likely to downgrade the recommendation when the company's price-to-earnings multiple approaches the 2-year low price-to-earnings multiple.*

Hypotheses 1-2 test the findings of Li et al. (2016) who point out in their working paper that the 52-week high stock price plays a significant role in analyst recommendation revisions. They find that analysts are more likely to downgrade recommendations when the stock prices approach the 52-week high levels. Nevertheless, they do not find statistically significant effect for the 52-week low stock price. I hypothesize that analysts are more likely to upgrade the recommendation when the company approaches the 52-week low stock price as analysts may see the stock price to hit a 'support level' so they consider that the stock price cannot go lower anymore. Nevertheless, Li et al. (2016) results indicate that the reaction for the 52-week low would be to the same direction as in the case of the 52-week high, i.e. when the company's stock price is approaching the 52-week low stock price, analysts would be more likely to downgrade the stock rather than upgrade. One explanation why analysts would behave this way in these low price points is that instead of underreacting to the news, they overreact. Overreaction could indicate that analysts are more momentum chasing in these situations.

Hypotheses 3-4 extend beyond existing literature, proposing that in addition to the known determinants of analyst recommendation revisions, the low (high) reference P/E multiple plays a significant role in analyst recommendation revisions. The main reference time period used is the 2-year time period but also other time periods are tested, the last 1, 3, 5 and 10 years. On top of that, in additional tests the correlations of P/E approach dummies are tested to other important market multiple dummies such as PEG ratio, EV/EBITDA, EV/EBIT and EV/Sales.

High correlation would indicate that similar results may be obtained by using one or many other market multiples, indicating that analysts may not potentially only anchor to historically high/low price-to-earnings multiple or 52-week high/low stock price. In robustness checks, regression tests are also run with these other market multiples with the 2-year time period.

1.2 Contribution to existing literature

There is vast amount of academic literature about analysts and their recommendations. Majority of papers focus on examining analyst and firm characteristics, analyst incentives and conflict of interests, analyst influence and informativeness of recommendations, momentum strategies and potential buy-and-hold returns. Only recently, there have been more studies on the behavioral biases that analysts face when making their recommendations. For example, Li et al. (2016) find that analysts partly anchor their views on the 52-week high reference point. Similar effect for the 52-week low point is not found.

Academic literature has long evidenced that also professionals suffer from common biases, e.g. study of stockbrokers (Staël Von Hosltein, 1972) and study of overconfident investors (Barber and Odean, 1999) to cite a few. To some extent people learn to avoid biases but learning is often too hard and individuals who consider themselves experts in a particular area may be slow to adjust their decision making (For discussion, see Hirshleifer, 2001).

However, to my best knowledge there is no single study in major academic papers that would examine the potential anchoring effects of valuation multiples in the light of analyst stock recommendations. This is surprising since analysts often use valuation multiples to evaluate the company's value. Demirakos et al. (2004) find evidence that analysts particularly refer to simple P/E multiples to support their stock recommendations. Bradshaw (2002) finds that analysts rely less on present value techniques to support their recommendations. The author also finds that analysts most often support their recommendations by referring to P/E ratios and long-term growth rate forecasts, implying that both P/E ratio and long-term growth ratio are used in the recommendation decisions. Bradshaw (2002) concludes that forward-looking PEG ratio is an important heuristic used by analysts to convert their earnings forecasts into target prices forecasts and recommendations.

Nevertheless, there might be another explanation for the extensive use of valuation multiples by analysts. Analysts may choose to communicate with investors with simple heuristics that correlate with analysts' more complex valuation models. Bradshaw (2002) summarizes that analysts may use other valuation techniques but simply refer to PEG ratio to justify recommendations or use models that are correlated with the PEG ratio.

What makes the topic more interesting, it is empirically studied that valuation multiples may be useful in forecasting future stock price changes. Liu et al. (2002) show that multiples based on forward earnings explain stock prices better than multiples based on historical earnings. Furthermore, Campbell and Shiller (1998) study long-term P/E ratios and find that these ratios have been useful in forecasting future stock price changes. However, the findings may just as well be the results of coincidence and data mining. Still, these kinds of findings may have profound effects on analysts' decision making, leading analysts to think multiples have predictive power.

All in all, the topic is fascinating since there is no prior research available and analysts often justify their recommendations with simple valuation multiples, indicating that they may use these valuation multiples to reach their recommendations. Additionally, recommendations are forward looking which means that these predictions always include uncertainty. Furthermore, not only the recommendations contain an intuitive component but there is always time pressure to make recommendations – constantly changing stock prices and limited amount of time dedicated to make the recommendations. With bounded rationality and judgment under uncertainty, analysts are prone to use simple heuristics not only to communicate with investors but also to revise their recommendations.

1.3 Scope of the study and potential limitations of the study

The sample consists of 35,270 analyst recommendation revisions from 5,193 analysts for 1,454 unique US stock-listed companies. My sample consists of recommendation revisions in the period of November 1993 until September 2015 since recommendation database is scarce before November 1993. My data includes all U.S. stocks with sufficient data available. Earnings estimates must be positive and there should be outstanding forward-looking earnings estimates in the past three years on a monthly basis in order to be included in the sample. The procedure ensures that the stocks are of sufficient interest to investors and makes it possible to calculate meaningful, longer term low points of P/E and other valuation ratios. However, the sample may bias the results so that it may not be representative of the many firm-years excluded from the sample. My sample size is also substantially smaller to Li et al. (2016) because their focus is only on the 52-week high and low phenomena and thus they do not use the earnings estimates to calculate long-term P/E ratios.

This thesis focuses on the effect of P/E ratios derived from consensus earnings estimates. Brown et al. (2015) find that existing literature suggests that analysts incorporate other analysts' forecasts and recommendations in their own forecasts and recommendations. However, the authors do find contradicting evidence on the use of consensus estimates but the use of analysts' own estimates is left outside of the scope of this thesis. What is more, Bradshaw (2011) finds that there is only limited evidence on what analysts do with their own forecasts.

As analyst recommendations are forward looking, it is most meaningful to look for forward-looking valuation ratios as well. The results are more likely stronger with forward-looking ratios because multiples based on forward earnings explain stock prices better than historical ones (See e.g. Liu et al., 2002). Furthermore, this thesis focuses on company-specific valuation multiples. Impact of industry-wide ratios is left outside the scope of this thesis.

1.4 Main findings of the study

I find that analysts partly anchor their recommendation revisions to the 52-week high and low stock prices. Furthermore, analysts may also partly anchor their revisions to the 2-year high and low P/E ratios as well as to their own target prices. However, in the case of P/E ratios and target prices, the magnitude of the effect is smaller and results are statistically significant only at the 5 or 10% level when the 52-week high and low phenomena are controlled. My results show that analysts tend to downgrade stock recommendations near these reference points. The odds of being downgraded by analysts are over 40% higher for stocks approaching the 52-week high or low than that for other stocks in the main tests. Thus, the results indicate that the reference points based on historical stock prices have a larger effect on the analysts' recommendation revision decisions than reference points based on valuation multiples.

The findings are partially consistent with prior literature. Li et al. (2016) find similar reaction with the 52-week high stock price but they do not find statistical significance for the 52-week low reference point. However, academic literature is mixed on the effect of the 52-week low as there are also many papers suggesting that 52-week low is an important anchor for investors and e.g. George and Hwang (2004) find negative abnormal returns for stocks that trade near the 52-week low. Furthermore, one could argue that if the 52-week low stock price is an important anchor for investors, it is also important for analysts because analysts' beliefs are seen as a good proxy for the beliefs held by investors in general (Bradshaw, 2011).

My results show that analysts may partly anchor their views on the P/E multiples or PEG ratio but similar effects are not found from Enterprise value multiples of EV/EBITDA, EV/EBIT or

EV/Sales when all controls are included and also the 52-week high and low phenomena are controlled. The results are consistent with prior literature which states that analysts often justify their recommendations by using P/E or PEG ratios (Bradshaw, 2002). With all control variables included, the odds of being downgraded by analysts are 14.8% and 19.6% higher for companies when the P/E ratio is approaching the 2-year high and 2-year low P/E, respectively. The magnitude is substantial but over two times smaller compared to the 52-week high and low phenomena where the odds of being downgraded are over 40% higher in both cases.

Furthermore, when the company's P/E ratio is approaching the 2-year low P/E and the stock price is approaching the 52-week low stock price, the effect on downgrade is inverse compared to earlier results and thus the analyst is more likely to upgrade the recommendation in these reference points. One potential explanation is that the combination of low valuation ratios and low stock price leads the analyst to think that the stock has hit a 'support level' which leads the analyst to underreact to company-specific negative earnings news. The analyst may think that the stock price cannot continue to drop much further.

Lastly, it is to be noted that the anchoring effect on the P/E ratio loses statistical significance in a robustness check where regressions are run separately for each weekday. The same holds true for the two most important control variables that seem to have the greatest effect on downgrades. These control variables yield statistically significant results at the 1% level in the main tests. A stock's recent price momentum in the previous weeks (cumulative return between trading days t-21 and t-6 before the recommendation revision day t) seem to increase the odds of downgrading substantially whereas an increase in the sum of prior six months' earnings forecast revisions (scaled by price) seem to decrease the odds of downgrading substantially. However, the anchoring effects near the 52-week high and low stock prices remain statistically significant in all robustness checks, indicating that analysts would partly anchor their recommendation revisions to these price points and that the findings would not only be outcomes of coincidence and data mining.

1.5 Structure of the paper

The thesis is organized as follows. Chapter 2 provides a literature review on key academic papers and themes. Chapter 3 describes the data and data gathering methods and possible limitations of the data while Chapter 4 discusses the methodology used in this study. Chapter 5 shows empirical results and includes a discussion of results. Chapter 6 concludes and provides suggestions for further research.

2. Literature review

This chapter summarizes prior research in related fields of behavioral finance and analyst stock recommendations. Despite the vast amount of literature on analysts, only a small portion of studies has focused on the behavioral side of analysts. First section discusses the framework of judgment under uncertainty which affects analysts and their decision making. The next sections include discussions of relevant psychological biases such anchoring and adjustment, prospect theory and investor attention. These theories may partly explain findings on the 52-week high and low phenomena. Valuation methods, herding and momentum effects as well as relevant analyst stock recommendation literature are discussed in the remaining sections.

The behavioral finance literature covers a wide range of biases for which investors can be prone to. A good review of literature from investor perspective is provided by Hirshleifer (2001). Another good overview of psychological biases of investors is provided by Baker and Nofsinger (2002). They divide biases into two sections: how investors think (1) and how investors feel (2). Table 1 provides an overview of the main biases.

Table 1. Psychological biases of investors

This table represents an overview of psychological biases faced by investors as in Baker and Nofsinger (2002). Biases are divided into two main sections: how investors think (1) and how investors feel (2).

How investors think (1)	How investors feel (2)
Representativeness bias	Disposition effect
Cognitive dissonance	Attachment bias
Overconfidence	Changing risk preferences
Reference points and anchoring	Social effects on the investor
Mood and optimism	The media
Familiarity bias	Social interaction and investing
Endowment effect	The Internet
Status quo bias	
Law of small numbers	
Mental accounting	

2.1 Analysts' judgment and decision making under uncertainty

Due to limited amount of time, information and cognitive abilities, people cannot analyze all of the data and options but instead use rule-of-thumbs, heuristics, to simplify decisions (Simon, 1955). The heuristics that people use are often similar which leads to systematic rather than random biases. Experimental psychology has long evidenced systematic biases in situations where uncertainty and intuition is involved. Tversky and Kahneman (1974) find that the general characteristics of judgment under uncertainty are the reliance on heuristics and the presence of common biases. One situation where intuition and uncertainty is involved in the judgment is analyst stock recommendations. However, it is worth questioning whether the analysts' intuition is worth the trust?

Intuitive judgment is sometimes flawed but it can arise from genuine skill. Kahneman and Klein (2009) describe two approaches to intuition and expertise: heuristics and biases (HB) and naturalistic decision making (NDM). NDM is based on the view that professional judgment can be based on skill and expertise and that experts use cues successfully to make their judgments. For example, Chase and Simon (1973) show that great chess players can recognize a good move without calculating all potential moves. The intuition is based on the recognition of patterns stored in memory. In contrast to NDM, the HB approach focuses more on the flaws of intuition leading to systematic biases in decision making. Therefore, intuitive judgment arises from simplifying heuristics, not from specific experience.

When it comes to analysts and their judgment, both approaches to intuition and skill are appropriate and applicable in some situations. According to Kahneman and Klein (2009), skilled intuition can develop in an environment with sufficiently high validity and additionally there needs to be suitable opportunity to train the skill. These criteria can be met for example in some mergers and acquisitions situations[5] which are familiar for the analyst. From early on, the analyst using his vast knowledge in the company, industry and earlier transactions may often successfully determine rather accurately the valuation range for which the deal would go through. The analyst uses his intuition in a situation where the environment is sufficiently regular and his intuition is rooted in previous similar experiences.

Nevertheless, analysts can unlikely develop skilled intuition for stock recommendations. Kahneman and Klein (2009) find that professionals with expertise in some specific area may unsuccessfully try to apply their skills in other areas of their work where actually a different environment exists. Therefore, even though the analyst knows how to use his intuition successfully for some purposes, the attempt to use the same knowledge for other purposes may misguide him. This is a fallacy that many finance professionals may fall down. Kahneman and Klein (2009) discuss that experienced professionals may become overconfident when they know a great deal about a particular company and have received good feedback supporting their confidence in performing short-term tasks while the feedback from their failures in the long-

[5] Analysts may face biases in these kinds of familiar mergers and acquisitions situations as well, such as anchoring. One anchoring example is described in Section 2.3 Reference points, anchoring and adjustment.

term judgments are often delayed, sparse and ambiguous. Additionally, they may make judgments that are successful by chance.

As Kahneman and Klein (2009) put it, to develop skilled intuition requires an environment of high validity and opportunity to learn the environment. Predictions of future value of individual stocks and long-term stock price performance are almost made in a zero-validity environment, assuming efficient markets. This leads to flawed intuitive judgment and use of heuristics to simplify decisions. The analyst may have skill to determine the commercial prospects of a firm but applying these skills to judge whether a stock is underpriced or overpriced goes beyond their skills. One explanation for this kind of behavior is overconfidence which can arise from applying expertise to areas where the professional has no real skill or from successful historical judgments.

2.2 Overconfidence and biased self-deception

Overconfidence and self-deception are related to anchoring and adjustment phenomenon observed also among analysts. Self-deception means that individuals are designed to think they are better and smarter than they really are (see Daniel et al., 1998). Griffin and Tversky (1992) find that professionals tend to be more prone to overconfidence than non-professionals when predictability is low and evidence is ambiguous, such as in the case of stock recommendations. According to their study, experts with rich models are even more likely to exhibit overconfidence.

Overconfidence is widely recognized phenomenon among experts in the financial markets[6]. One of the reasons is that estimating stock performance is an open-ended question and feedback is delayed. It can lead analysts to under- or overweigh information. The theory of overconfidence and self-deception would state that the analyst's confidence grows when public information is in agreement with his view but it does not drop considerably when public information is in disagreement with his private information.

There are lots of documented research that individuals tend to credit themselves for past successes and blame external factors for failure. Miller and Ross (1975) find that successful outcomes result in greater self-attribution of performance than failing or neutral outcomes. Taylor and Brown (1988) summarize psychological literature and discuss the findings that individuals have overly positive views of themselves, excessive belief in their ability to control

[6] See e.g. Odean (1998) for discussion of the overconfidence of traders.

their environment and a view that their future is far better than the average person's. Langer and Roth (1975) study purely chance-based tasks and find that the group with early successes in coin tosses increased their evaluation of past performance, over-remembering it. The people in this group tended to keep themselves significantly better at predicting future outcomes of coin tosses compared to other groups.

2.3 Reference points, anchoring and adjustment

Tversky and Kahneman (1974) refer to anchoring when people make estimates by starting from an initial value which is then adjusted to yield the final answer. However, they find that these adjustments are usually insufficient and different starting points yield different estimates which are biased towards the initial values. In other words, the initial value carries an unreasonably high weight in the person's decision-making process. In the stock market, anchoring can mean for e.g. locking your view into a reference point such as purchase price, specific historical stock price or relative metrics such as P/E ratio.

Reference points play a significant role in people's decision making even though these price points are often irrelevant numbers. 52-week high stock price is one of most widely documented reference point. George and Hwang (2004) find evidence that 52-week high serves as a reference point for investors. They find underreactions in stock prices when stock prices are approaching 52-week high even if stocks have had very high past returns.

Baker et al. (2012) find that reference points play a critical role in mergers and acquisitions. They find that prior stock price peaks, such as 52-week high, affect several aspects of merger and acquisition activity and pricing. Value estimations for the company may be anchored to companies that are viewed similar and bias the sample that comes to mind. The same can happen for stock market analysts. For example, when an analyst is following Google, his recommendation revisions may be anchored mainly to the changes in stock prices and price/enterprise multiples of Microsoft and Apple. The analyst may view Google similar to these two other companies as they are both in the same high-tech industry and thus when estimating future stock price of Google, the sample that comes to analyst's mind may only include these two other companies even though there could be several other important peers from different industries for instance.

In the context of analyst stock recommendations, a reference point can be past stock price such as historical high or relative metrics such as price-to-earnings ratio. A reference point formation can happen for example when there is an unexpected earnings announcement. This should lead analysts to adjust their recommendations to fully reflect the new information. However, as the analyst has anchored his view on a reference point, the adjustment does not fully reflect the new information and adjustment is insufficient. Li et al. (2016) find evidence that 52-week high stock price may serve as a reference point for analysts.

Another anchoring definition is by Chapman and Johnson (1999) who state that anchoring is a pervasive judgment bias where decision makers are systematically influenced by random and uninformative starting points. They summarize plenty of anchoring literature and find that anchoring effect has been widely found in studies of judgment such as pricing and rating of simple gambles, estimation of probabilities and answers to factual knowledge questions. Furthermore, anchoring is also present in e.g. false consensus effects and predictions of future performance. Chapman and Johnson (1999) study anchoring as activation and find that anchor biases the information used in the target evaluation because it leads activation of selective target information that is consistent with the anchor. They find that anchoring effect is reduced when subjects are prompted to consider features of the item that are different from the anchor while prompting subjects to consider similar effects to anchor has no effect.

Prospect theory of Kahneman and Tversky (1979) finds that gains and losses are evaluated relative to a reference point and that investors have extra aversion to losses at the reference point. Value function is convex for losses and concave for gains and investors tend to overweight low probability events. Hirshleifer (2001) describes loss aversion as a phenomenon in which people tend to be averse to even to very small risks relative to a reference point. Kaustia (2010) shows that prospect theory unlikely explains the disposition effect. Disposition effect means that people are more willing to recognize gains than losses.

Barber and Odean (2008) discuss the investor attention hypothesis which states that investors focus on the information that have caught their attention. According to Barber and Odean (2008), individual investors have limited capabilities to follow all stocks and thus they focus on a subset of stocks that grab their attention. Yuan (2015) finds that market-wide attention affects individual investors’ trading behavior. Yuan (2015) shows that high market attention leads individual investors in aggregate to reduce their stock positions substantially when the market index is high and modestly to increase when the market index is low.

2.4 Momentum strategies and 52-week high/low as reference points

Momentum strategies take advantage of investor underreactions and stock prices fail to adjust adequately (Jegadeesh and Titman, 1993). Jegadeesh and Titman (1993) find that momentum strategies of buying stocks with good past performance and selling stocks with poor past performance generate significant positive returns over 3- to 12-month holding periods. There is also empirical evidence that momentum strategies based on analyst stock recommendations are working. Barber et al. (2001) and Jegadeesh et al. (2004) find significant profits from calendar timing trading strategies based on the level of analysts' recommendations. Trading strategies based on purchasing the most recommended quintile of stocks and sell the least recommended quintile of stocks generate abnormal returns.

Furthermore, Jegadeesh et al. (2004) find that price and earnings momentum are correlated with recommendation levels but that recommendation revisions based strategies are not driven by momentum or any other stock characteristics. Nevertheless, Barber et al. (2010) find that methods of Jegadeesh et al. (2004) do not fully capture the value of analyst recommendations. They provide evidence that both rating levels and rating changes have incremental predictive power for security returns.

Barber et al. (2010) show that superior returns are yielded with hedge strategies of buying single (double) upgrades to buy or strong buy and shorting those receiving single (double) downgrades to sell or strong sell. These returns are superior to the strategies of change only (buying all single upgrades and shorting all single downgrades) and levels only (buying all buys and strong buys and shorting all sells and strong sells). When analyzing the effect of firm size, small stocks dominate the returns and no evidence of superior returns are found with large cap stocks.

George and Hwang (2004) find that 52-week high stock price explains partly the profits from momentum based investment strategies. Their results suggest that 52-week high stock price has predictive power even if individual stocks have had high past returns. Investors also seem to anchor to the 52-week high when evaluating the potential impact of news. George et al. (2015) show that investors anchor their beliefs on the 52-week high stock price which restrains price reactions to earnings news close to the 52-week high. They find that the post earnings announcement drift is dependent on the 52-week high when earnings surprises arrive. In addition, Li et al. (2016) find positive abnormal returns on taking a long position on stocks approaching the 52-week high stock price.

Many studies have examined momentum strategies of 52-week low and find positive abnormal returns. Huddart, Lang, and Yetman (2009) find that hitting the 52-week low generates positive abnormal returns. George and Hwang (2004) find negative abnormal returns for stocks trading close to their 52-week low stock price. Brock, Lakonishok, and LeBaron (1992) show that hitting the past 200-day low stock index generates negative abnormal returns.

2.5 Valuation multiples used by analysts

Gleason et al. (2013) discuss that stock valuation methods can be divided into two categories: fundamental valuation models such as discounted cash flow method and relative valuation models such as P/E multiples and P/B multiples which are compared to historical norms or other companies in the same industry. According to Gleason et al. (2013) these valuation multiples are derived from informal methods and experience and are easy to apply and communicate which is in line with e.g. Bradshaw (2002) and Liu et al. (2001). Furthermore, Bradshaw (2004) finds that residual income models are unrelated or negatively related to recommendations whereas PEG ratio is positively related to recommendations.

Analysts regularly use and cite valuation multiples. Demirakos et al. (2004) find evidence that analysts most often refer to P/E multiples to support their stock recommendations. Bradshaw (2002) finds that analysts rely less on present value techniques to support their recommendations. The author finds that analysts most often justify their recommendations with references to P/E multiples and long-term growth rates, indicating that both ratios are supporting the analyst's recommendation or valuation decision. Bradshaw (2002) concludes that forward-looking PEG ratio is an important heuristic used by analysts to convert their earnings forecasts into target prices forecasts and recommendations.

Demirakos et al. (2004) examined 103 analyst reports and find that 67% of analysts use valuation multiples while discounted cash flow model is used by 16% of analysts and residual income models by 10% of analysts and other approaches by 7% of analysts. Pinto et al. (2015) provide a summary of previous survey-based studies on equity valuation. Pinto et al. (2015) find that in Americas 92.6% of the survey respondents use a market multiples approach for valuation which is clearly the most common method in their survey. Ranking second and third are discounted cash flow model (73.9%) and asset-based approaches (59.5%). Pinto et al. (2015) show that among those who use market multiples in the Americas, the most popular multiples are the P/E (87%) and enterprise value multiples (76%). Furthermore, Barniv et al. (2010) show that stock recommendations correlate negatively to residual income valuation estimates but positively to valuation heuristics based on the PEG ratio and long-term growth rate.

Liu et al. (2001) study the most commonly used multiples and find that multiples based on forward earnings explain stock prices the best and are more value-relevant compared to historical earnings measures, cash flow measures and book value and sales measures. Moreover, results of Wu (2014) with forward P/E ratio are consistent with Liu et al. (2001). Wu (2014) also summarizes well the crucial role of P/E ratio in the investment community: P/E ratio reflects the market expectations of future growth and firm risk and it can be used to estimate cost of equity and earn excess stock returns from glamour/value anomaly.

2.6 Abnormal returns and analyst stock recommendations

There is vast amount of academic literature on analyst stock recommendations and plenty of evidence that abnormal returns can be made by following analyst stock recommendations in the US stock market, indicating that stock recommendations have informational value. In one of the most cited papers, Womack (1996) finds that returns in the three-day recommendation period are large and in the direction forecast by the analysts. The results go in line with the expanded view of market efficiency proposed by Grossman and Stiglitz (1980). They suggest that returns are required due to information search costs.

On the other hand, the empirical results may be in contradiction with the foundation of modern financial theory, the Efficient Market Hypothesis, proposed by Malkiel and Fama (1970). It states that in efficient markets stock prices reflect all available information. In the semi-strong form of market efficiency, prices reflect all publicly available historical and current information and thus there should not be excess returns to be made by following analyst stock recommendations since the information is already reflected in the stock prices. However, it is important to keep in mind that all these empirical studies on abnormal returns are always open to criticism since it may be that the expected return benchmark used in measuring abnormal returns may be misspecified as discussed by Fama (1998).

Majority of research has focused on studying when the recommendations are most powerful. Stickel (1995) finds that recommendation upgrades tend to outperform downgrades. Furthermore, changes in recommendations that skip a rank have a greater price effect than changes in recommendations that do not skip a rank. Also, larger brokerage houses have more impact on prices than do smaller brokers, which is consistent with larger houses having stronger marketing staff. Boni and Womack (2006) as well as Green (2006) document that stocks that are most favorably recommended outperform the stocks with the least favorable recommendations.

Barber et al. (2010) provide evidence that abnormal returns can be made when analysts' recommendation rating levels and rating changes are followed. They conclude that investing based on both levels and changes has the potential to outperform one based exclusively on one or the other. Furthermore, they find that recommendation levels and revisions may help forecast future unexpected earnings and resulting market reactions.

Analyst characteristics are also extensively studied. Loh and Stulz (2011) examine influential recommendation changes in terms of visible stock price impact. They find that recommendation changes are more likely to be influential if they are from leader, star, previously influential analysts, issued away from consensus, accompanied by earnings forecasts, and issued on growth, small, high institutional ownership or high forecast dispersion firms.

Boni and Womack (2006) examine value of analysts as industry specialists. They show that analysts create value in their recommendations mainly through their ability to rank stocks within industries. They suggest that aggregate recommendations of any firm that provides research coverage that is widely diversified across industries should be expected to outperform those of any firm that covers only a few industries. They conclude that recommendation information is quite valuable for identifying short-term within industry mispricing but this same information aggregated by industry is not of obvious value in projecting future relative returns across industries.

It is also shown that the reactions are largest in the US stock market. Jegadeesh and Kim (2006) show that stock prices react significantly to recommendation revision in G7 countries except Italy. They document the largest price reactions around the recommendation revisions and post-revision price drift in the US. They conclude that most likely explanation to superior performance in the US market is that analysts in the US market are more skilled at identifying mispriced stocks than their foreign counterparts. Their explanation for this is that salaries are highest among US analysts which could indicate that US analysts are most skillful and thus explain the strongest market reactions.

2.7 Selection bias, herding and incentives in analyst stock recommendations

Selection bias is present in analyst recommendations. Womack (1996) finds that recommendations are mainly issued on well-followed large capitalization stocks. Boni and Womack (2003) find that growth stocks are valued over value stocks. Loh and Mian (2006) document that analysts prefer glamour stocks. They find that stocks that are given higher recommendations tend to have positive momentum and high trading volume. They also exhibit greater past sales growth and are expected to grow their earnings faster in the future. These stocks also tend to have higher valuation multiples, more positive accounting accruals, and capital expenditures constitute a greater proportion of their total assets. Loh and Mian's results also hint that analysts could improve their stock recommendations if they paid more attention to the relation between stock characteristics and future returns.

There is also a plenty of discussion of potential conflicts of interests of analysts. According to Barniv et al. (2010), analysts in the research department who provide stock recommendations may feel pressure from the investment banking division to provide favorable reports because unfavorable reports may reduce investment-banking business of the brokerage firm. According to the authors that is one of the reasons why SEC accepted new regulations in the US in 2002 to limit interactions and flow of information between these two departments. Brown et al. (2015) provide good insights into incentives analysts face by surveying 365 analysts covering a wide range of topics. They find for example that industry knowledge is an important factor to determine analysts' compensation. In addition, generating underwriting business and trading commissions continues to be an important part of compensations for many analysts. This is in line with Michaely and Womack (1999) who report significant evidence of recommendation bias of underwriter analysts. They show that the stock performs better when it receives a buy recommendation from an unaffiliated broker and worse when the stock is recommended by underwriter analysts.

Jegadeesh and Kim (2010) discuss the herding effects among analysts. They show that analysts herd near the consensus when they issue stock recommendations. Results indicate that the market recognizes analysts' tendency to herd since the stock price reactions are stronger when the new recommendation is issued away from the consensus than when it is closer to it. Booth et al. (2014) study who lead the herd in stock recommendations. They find that recommendations are more likely to affect the direction of consensus in the following conditions: they are issued by lead analysts accompanied by concurrent earnings forecast that are in the same direction from the same analysts, away from the consensus, followed by price momentum, issued on large and high-growth firms and issued by analysts from large brokers with less frequent recommendations. Furthermore, market reactions are stronger for the recommendations of lead analysts than others.

3. Data

This chapter describes the data, goes through data gathering process and possible limitations of the data. IBES, CRSP and Compustat data are retrieved via Wharton Research Data Services (WRDS). First section describes the IBES data gathering process. Second section discusses the CRSP stock exchange data and Compustat accounting data gathering processes. Third section provides an overview how these databases are combined and fourth section shows descriptive statistics of the data. In the last section of this chapter, possible limitations of the study are discussed.

3.1 Analyst stock recommendations and forecasts from IBES

Analyst stock recommendations were gathered from IBES database. IBES recommendation data is scarce and incomplete before November 1993 (see e.g. Demiroglu and Ryngaert, 2010) which is why data before November 1993 is not used. This study focuses solely on US companies listed in NYSE, AMEX and NASDAQ stock exchanges. To ensure data validity, observations with missing analyst name or masked analyst code were removed. Stale recommendations were removed, i.e. recommendations that are older than one year, specifically if the IBES review date is over one year later than the announcement date. Review date is the most recent date on which IBES verified that a particular recommendation was still valid by calling the analyst. If the analyst confirms that a previous recommendation is valid, the original database record for that recommendation is retained and only the review date variable updated (Booth et al., 2014). Recommendations that have review date or activation date before announcement date were removed. Recommendations dated between 2.9.2002-10.9.2002 were removed due to changes in recommendation categories (Kadan et al. 2012, Loh & Stulz 2011).

Bradley et al. (2014) point out that recommendations' timestamps in IBES are delayed by approximately 2.4 hours although the majority of recommendations with delayed announcement times occur before the market opens. After correcting for timestamp delays, they find significant intraday market reactions to the recommendations. As I have no access to the newswires to compare the actual timestamp to the IBES recorded one, I have no possibility to separate the recommendations that are actually announced at trading hours and which are not. Thus, in my study recommendations that occur after trading hours are interpreted as if the event day had occurred that day.

If multiple recommendations are issued by the same analyst to the same company on one day, only the latest record is kept. If multiple analyst recommendations are given on the same day for the same company, potential herding effect is controlled by using Analyst herding dummy defined in Table 5. Multiple academic studies have found herding among analysts. For discussion of herding effects among analysts, see e.g. Jegadeesh and Kim (2010).

Recommendation levels are reversed to help interpretations so that *Strong buy* recommendation corresponds 5, *Buy* to 4, *Hold* to 3, *Underperform* to 2 and S*ell* to 1. After the reversion, recommendation upgrade corresponds to a positive value and recommendation downgrade a negative one. Reiterations and initial recommendations are removed from the sample, which is one commonly used approach by researchers. Also Li et al. (2016) test their results excluding reiterations and initial recommendations.

I use IBES summary statistics file to find the companies that analysts have followed and given EPS forecasts for next and current fiscal year. The dataset includes one observation per month for each company. Each observation includes the median and mean estimates based on all the analysts that have outstanding estimates for the company in question in the past month. When the announcement date of the actual is missing, data is excluded from the sample. Furthermore, companies with less than 5 years of earnings estimates are dropped as I need to calculate longer-term price-to-earnings ratios. Furthermore, consecutive three years of positive median EPS estimates are required to be included in the sample. That means that in the recommendation revision month, there needs to be at least three years of consecutive positive monthly EPS estimates to calculate meaningful 3-year low and high P/E ratios and thus approach dummies.

3.2 Stock exchange data from CRSP and accounting data from Compustat

Stock exchange data is retrieved from CRSP database. Share code must be 10 or 11 implying common shares. In addition, exchange code must be 1, 2 or 3, indicating NYSE, AMEX and NASDAQ stock exchanges, respectively. Market capitalization on day t is calculated as common shares on day t multiplied by the closing price on day t. Observations with missing market capitalization are dropped. Price and share data is adjusted for stock distributions.

Accounting data is retrieved from Compustat Annual Update. Below, Table 2 describes the data variables collected. The control variables used in this study are further defined in Chapter 4. For each observation, the most recent Compustat data available is used which is based on the reported quarterly/annual earnings announcement dates. The data is considered available for analysts based on the announcement dates reported in Compustat database.

Table 2. Compustat accounting data

This table shows the main variables retrieved from the Compustat database, including both quarterly and annual data.

Variable	Frequency	Definition
ebitda	Annual	Annual earnings before interest, taxes, depreciation and amortization
ebit	Annual	Annual earnings before interest and taxes
revt	Annual	Annual sales
at	Annual	Total assets at the end of the fiscal year
epsfx	Annual	Annual earnings before extraordinary items, diluted
capxq	Quarterly	Quarterly capital expenditure
saleq	Quarterly	Quarterly sales
dlttq	Quarterly	Total long-term debt at the end of the quarter
dlcq	Quarterly	Debt in current liabilities at the end of the quarter
mibq	Quarterly	Noncontrolling interest, redeemable, balance sheet
pstkq	Quarterly	Total preferred/preference stock capital
cheq	Quarterly	Cash and short-term investments
atq	Quarterly	Assets at the end of the quarter
ceqq	Quarterly	Total common/ordinary equity
epsfx	Quarterly	Earnings before extraordinary items, diluted
actq	Quarterly	Current assets, total
lctq	Quarterly	Current liabilities, total
oancfy	Quarterly	Net cash flow from operating activities
ibq	Quarterly	Income before extraordinary items
txpq	Quarterly	Income taxes payable
dpq	Quarterly	Depreciation and amortization expense

3.3 Linking databases

To link CRSP stock data and IBES analyst forecast and recommendation data, I use commonly used CUSIP method to link company tickers (IBES tickers and CRSP PERMNOs). IBES uses historical CUSIPs and CRSP the most recent one so to link the companies, the latest CUSIP for each company are obtained from the IBES database.

Linking by CUSIP is very effective as it produces a large number of potentially accurate matches according to WRDS.[7] This is because CUSIPs are not reused over time, i.e. the CUSIP code is not assigned to other companies after original company is delisted for instance. Thus, linking with CUSIP is not expected to yield many inaccurate matches. WRDS tested this method and they were able to link 94% of US companies in the IBES database as of April 2006 (14,591 links).

WRDS has created a 'CCM' linking table (CRSP/Compustat Merged Database) to combine CRSP and Compustat data using CRSP's PERMNO or PERMCO codes or using Compustat's main identifier GVKEY. Although linking is highly accurate, it is not complete or entirely

[7] Linking IBES and CRSP Data via webpage https://wrds-web.wharton.upenn.edu/wrds/support/Data/_010 Linking%20Databases/_000Linking%20IBES%20and%20CRSP%20Data.cfm. Accessed 15.09.2016 (requires log-in). See the page also for alternative methods to create IBES-CRSP links.

unambiguous according to WRDS[8]. For instance, the match between Compustat's main identifier, GVKEY and CRSP's PERMNO is not one-to-one because a company might have multiple equity issues and thus a single GVKEY links to all the associated equity issues. Only those observations with research complete (link type code = LC) and unresearched link to issue by CRSP (LU) are used in the CCM linking table. The latter link is established by comparing the Compustat and historical CRSP CUSIPs. WRDS refers to these links as primary. Other link types are either irrelevant for this study (ETFs, indices) or not verified (secondary link types), and thus are excluded. I use the PERMNO company list to retrieve all the associated GVKEYs from the CCM linking table.

For the 10,612 unique permno codes in the IBES/CRSP dataset, CCM linking table retrieves 10,781 unique PERMNO - CUSIP and 10,781 unique PERMNO - GVKEY pairs. This means that the there are multiple occassions where one PERMNO links to multiple GVKEYS or multiple CUSIP codes. Thus to match correctly IBES/CRSP dataset with Compustat, I use both PERMNO and most recent CUSIP codes in order to obtain Compustat main identifier GVKEY to my dataset. The most recent 9-digit CUSIP code obtained from the CCM file is translated to 8-digit. In the merged file, there are 10,193 unique permno codes left, which means that the matching succeeded for 96% of the companies with this method.

When retrieving additional data, the permanent identifiers in each of these databases are used, i.e. PERMNO codes for CRSP data, GVKEYs for Compustat data and IBES ticker for IBES data. Before combining stock price data, accounting data or analyst forecast data, there are 216,511 recommendation revisions in the recommendation dataset with combined identifiers to all three databases. Nevertheless, the sample set becomes substantially smaller after applying the limitations for the data. The analyst forecast data is the main limiting factor of the sample as positive EPS forecasts are required on a monthly basis.

3.4 Description of data

The sample consists of 35,270 analyst recommendation revisions from 5,193 analysts for 1,454 unique companies during the period from November 1993 to September 2015. Table 3 provides description of summary statistics and Table 4 shows correlations between the most important variables.

[8] CCM Overview of CRSP/Compustat Merged Database via website https://wrds-web.wharton.upenn.edu/wrds/research/applications/linking/CRSP_COMPUSTAT_merged/index.cfm. Accessed 20.9.2016 (requires log-in).

Table 3 shows the mean, standard deviation, median and number of observations in the full sample. There are 35,270 recommendation revisions with a mean prior rating of 3.583. Li et al. (2016) full sample includes 214,691 recommendation revisions including reiterations with a mean prior rating of 3.570 which is close to my sample. My sample does not include reiterations and their corresponding subsample includes 121,158 revisions excluding reiterations. However, summary statistics from their subsample are not available. The inclusion of reiterations mainly explains the difference in the mean of downgrades that is 0.530 in my sample and 0.413 in Li et al. (2016) sample. Table 4 shows that there is statistically significant correlation between most of the variables and it is noticeable that correlation between Coverage and Size is high (0.704). However, majority of variables show correlation which is rather low between -0.1 and 0.1. This is in line with Li et al. (2016) dataset.

Other summary statistics seem to be robust with Li et al. (2016) as well. However, majority of my variables are tilted upwards compared to Li et al. (2016) due to excluding negative P/E ratios from my sample and reiterations. Furthermore, my sample includes only observations that have had three years of consecutive earnings estimates on a monthly basis given by analysts to ensure sufficient interest of analysts and investors and to calculate longer term P/E ratios on a daily basis. As a result, for instance variables *Size*, *Turnover*, *Analyst Coverage* and *Firm age* of the companies in my sample are much higher compared to Li et al. (2016).

Table 3. Summary statistics

The sample consists of 35,270 analyst recommendation revisions from 5,193 analysts for 1,454 unique companies in the period from November 1993 to September 2015. Recommendations range from 1 to 5, indicating sell, underperform, hold, buy and strong buy respectively. Recommendation revision is the current rating minus the prior rating for the firm by the same analyst. Downgrade equals 1 for recommendation downgrades and 0 for upgrades. Approach variables are dummies that equal 1 when the measure is 5% below (above) the high (low) value at day t-1 and 0 otherwise. For instance, specifically approach 52-week high stock price is 1 if (1-0.05) x 52-week high < price at t-1 < 52-week high and 0 otherwise. Other variables are defined in detail in Table 5 except firm age. Firm age is the recommendation announcement year minus the first year that the firm appears in CRSP plus one year. All continuous variables are winsorized at the 1% and 99% percentiles to eliminate outliers similarly to Jegadeesh et al. (2004).

	Mean	Standard deviation	Q1	Median	Q3	N
Prior rating	3.583	1.016	3	4	4	35,270
Recommendation revision	-0.091	1.485	-1	-1	1	35,270
Downgrade	0.530	0.499	0	1	1	35,270
Approach 52-week high stock price	0.152	0.359	0	0	0	35,270
Approach 52-week low stock price	0.054	0.225	0	0	0	35,270
Approach 2-year high P/E ratio	0.050	0.217	0	0	0	35,270
Approach 2-year low P/E ratio	0.036	0.185	0	0	0	35,270
Price/52-week high	0.812	0.177	0.717	0.859	0.952	28,370
Price/52-week low	1.403	0.455	1.137	1.294	1.527	28,370
P/E	25.165	46.158	9.133	15.235	24.193	35,242
Forward-looking P/E ratio	16.597	9.146	11.298	14.549	19.198	35,270
$\text{Return}_{t-5,\ t-1}$	0.000	0.062	-0.030	0.001	0.031	34,761
$\text{Return}_{t-21,\ t-6}$	0.003	0.099	-0.049	0.006	0.055	34,322
$\text{Return}_{m-6,\ m-2}$	0.047	0.250	-0.097	0.037	0.173	31,990
$\text{Return}_{m-12,\ m-7}$	0.075	0.270	-0.084	0.055	0.202	30,555
Forecast revisions	0.000	0.019	-0.003	0.002	0.008	30,977
SUE	1.273	1.530	0.377	1.138	2.052	34,542
Size	22.102	1.694	20.847	22.105	23.313	34,300
B/M	0.451	0.332	0.238	0.375	0.573	34,926
Turnover	8.826	9.683	2.657	5.843	11.472	34,074
Accruals	0.007	0.051	-0.019	0.004	0.029	23,120
Capex	0.068	0.059	0.026	0.052	0.091	33,017
Sales growth	1.144	0.218	1.028	1.104	1.216	35,087
LTG	14.920	7.067	10	14	18	34,351
Idiosyncratic volatility	0.021	0.012	0.013	0.018	0.026	35,268
Institutional ownership	0.596	0.280	0.357	0.643	0.833	35,270
Analyst coverage	16.663	9.246	9	16	23	35,270
Analyst dispersion	0.144	0.193	0.040	0.080	0.160	35,182
Analyst experience	4.464	4.401	1	3	6	34,848
Firm age	26.807	20.655	11	20	36	35,270

Table 4. Pearson correlation matrix

Table 4 shows Pearson correlation matrix. Correlations that are statistically significant at the 5% level or less are in bold. Downgrade equals 1 for recommendation downgrades and 0 for upgrades. *Approach52* equals 1 when stock price is approaching 52-week high stock price, *Approach52low* equals 1 when stock price is approaching the 52-week low stock price, *Approach02* equals 1 when forward-looking P/E for the next financial year is approaching the 2-year high and *Approach02low* equals 1 when forward-looking P/E for the next fiscal year is approaching the 2-year low. Otherwise these dummies equal to 0. Other variables are defined in detail in Table 5.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
Downgrade (1)																							
Approach52 (2)	**0.054**																						
Approach52low (3)	**0.024**	**-0.101**																					
Approach02 (4)	**0.020**	**0.349**	**-0.045**																				
Approach02low (5)	0.002	**-0.073**	**0.369**	**-0.03**																			
Return$_{t-5,\,t-1}$ (6)	0.006	**0.142**	**-0.133**	**0.071**	**-0.082**																		
Return$_{t-21,\,t-6}$ (7)	**0.089**	**0.181**	**-0.150**	**0.078**	**-0.087**	**0.075**																	
Return$_{m-6,\,m-2}$ (8)	**-0.039**	**0.218**	**-0.155**	**0.074**	**-0.069**	**0.014**	**0.014**																
Return$_{m-12,\,m-7}$ (9)	**-0.023**	**0.050**	**-0.059**	**0.031**	**-0.028**	**-0.017**	**-0.026**	**-0.027**															
Forecast revisions (10)	**-0.059**	**0.127**	**-0.099**	**-0.02**	**0.034**	**0.033**	**0.067**	**0.391**	**0.211**														
SUE (11)	0.007	0.009	**-0.011**	-0.009	0.010	**-0.023**	-0.008	**0.033**	**0.118**	**0.066**													
Size (12)	**-0.027**	**0.100**	**0.023**	**0.062**	**0.053**	**-0.017**	**-0.020**	**0.047**	0.005	**0.074**	**0.033**												
B/M (13)	**0.033**	**-0.115**	**0.066**	**-0.05**	**0.012**	**-0.078**	**-0.129**	**-0.258**	**-0.194**	**-0.338**	**-0.125**	**-0.293**											
P/E (14)	-0.005	**-0.041**	**-0.040**	**-0.02**	**-0.017**	**0.027**	**0.020**	**0.100**	**0.081**	**0.068**	**-0.020**	**0.012**	**-0.099**										
Forward P/E ratio (15)	**-0.022**	**0.053**	**-0.084**	**0.064**	**-0.071**	**0.109**	**0.129**	**0.223**	**0.156**	**-0.033**	**0.051**	**0.071**	**-0.369**	**0.319**									
Turnover (16)	**0.022**	**-0.126**	**0.016**	**-0.06**	0.000	**-0.040**	**-0.070**	**-0.116**	0.003	**-0.161**	**0.178**	**-0.045**	**0.045**	**0.325**	**0.086**								
Accruals (17)	**0.014**	**-0.056**	**0.028**	**-0.02**	0.013	**-0.048**	**-0.035**	**-0.095**	**0.021**	**-0.055**	**0.024**	**-0.110**	**0.027**	-0.005	**-0.050**	**0.035**							
Capex (18)	-0.001	**-0.042**	-0.003	**-0.01**	**-0.017**	-0.007	**-0.015**	**-0.023**	**0.013**	**-0.059**	**-0.060**	**-0.044**	**-0.073**	**-0.039**	**0.029**	-0.008	0.005						
Sales growth (19)	0.010	**-0.036**	**-0.026**	**-0.04**	0.002	**-0.014**	**-0.011**	**0.040**	**0.210**	**0.086**	**0.133**	**-0.084**	**-0.122**	**0.125**	**0.097**	**0.171**	**0.113**	**0.155**					
LTG (20)	**0.012**	**-0.088**	**-0.054**	**-0.06**	**-0.026**	**-0.022**	**-0.012**	**0.077**	**0.193**	**0.065**	**0.146**	**-0.178**	**-0.262**	**0.244**	**0.382**	**0.261**	**0.071**	**0.145**	**0.398**				
Inst. ownership (21)	**0.014**	**-0.060**	**0.020**	**-0.03**	**0.015**	**-0.032**	**-0.046**	**-0.082**	**-0.073**	**-0.089**	**0.123**	**0.043**	**0.066**	**0.216**	**0.027**	**0.336**	-0.008	**-0.156**	**-0.029**	**0.025**			
Coverage (22)	**-0.023**	**0.049**	**0.026**	**0.026**	**0.029**	0.010	**0.016**	-0.011	**-0.013**	0.004	0.010	**0.704**	**-0.180**	0.010	**0.058**	**0.066**	**-0.074**	**0.182**	0.005	**-0.045**	-0.005		
Dispersion (23)	-0.002	**-0.055**	**0.015**	**-0.03**	-0.003	**-0.011**	**-0.028**	**-0.088**	**-0.064**	**-0.192**	-0.001	**0.179**	**0.194**	**0.130**	**-0.151**	**0.366**	-0.002	**0.106**	**0.048**	**-0.089**	**0.286**	**0.178**	
Experience (24)	**-0.018**	**0.035**	0.005	**0.039**	0.007	0.010	0.006	-0.009	**-0.035**	0.007	**-0.049**	**0.221**	**0.015**	**-0.053**	**-0.083**	**-0.080**	**-0.044**	**-0.027**	**-0.129**	**-0.192**	0.005	**0.123**	**0.058**

3.5 Possible limitations of data

There are a few limitations of data. Positive values for analysts' earnings and growth forecasts are required which means that results may not be representative of the many firm-years excluded from the sample. Furthermore, the methods analysts use may vary substantially, and the regression results are based on averages, which means that there might be many analysts whose recommendations are not biased by anchoring heuristics. When it comes to analyst characteristics, star analysts are not taken into account since star analyst data is not accessible for the whole sample period.

Furthermore, impact of industry-wide ratios is left outside of the scope. For instance, analysts may potentially anchor to industry P/E ratios. However, it would be difficult to study industry multiples since comparable firms would be selected in a mechanical way in academic studies while each analyst may use his/her own unique peer group as comparable firms. Thus, results would more likely to be weaker and less significant because situation-specific factors are not considered by researchers.

In addition, my study assumes that analysts form the views for their recommendations based on consensus earnings estimates rather than their own estimates. This is based on rationale that analysts benchmark their own earnings estimates to other estimates and take into account that market consensus is right on average which is also the basis for the efficient market hypothesis. Bradshaw (2011) concludes that there is only limited evidence on what analysts do with their own forecasts. Brown et al. (2015) find that existing literature suggest that analyst incorporate other analysts' earnings forecasts and recommendations into their own forecasts and recommendations. However, their own results contradict with the prior findings suggesting that analysts do not incorporate other analysts' forecasts. Nevertheless, anchoring on own estimates is left outside of the scope but it would be an interesting topic for further research to see, whether analysts anchor their recommendation revisions to P/E ratios derived from their own earnings forecasts.

4. Methods

This chapter describes the methodologies used in this study. In addition, variables used in regressions are defined in detail.

4.1 Regression tests

Regression tests are similar to Li et al. (2016) who analyze the predictability of anchoring effects on the 52-week high stock price. Logit regressions for downgrades are run as follows:

$$Downgrade_{j,t} = \beta_0 + \beta_1 Approach_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t} \quad (1)$$

where subscript j and t denote the recommendation revision j issued on day t. In Equation 1, dependent variable is Downgrade which equals 1 for recommendation downgrades and 0 for upgrades. Approach variable is a dummy which tests the anchoring effect on e.g. 52-week high stock price. In case of 52-week high, Approach is a dummy that equals 1 if stock price at day t-1 for stock j is within 5% below the 52-week high stock price. Valuation multiples and approach multiples are further defined in Section 4.2.

Vector X includes a set of control variables that are relevant. The detailed definitions of control variables are provided in Table 5. Furthermore, industry (based on 10 main SIC codes) and year fixed effects are controlled. Accruals, B/M, capital expenditure, earnings forecast revisions, long-term growth forecast, sales growth, SUE and turnover are calculated similarly to Jegadeesh et al. (2004), and the rest of the variables are calculated similarly to Li et al. (2016) except analyst experience. Analyst experience control variable tries to capture the analyst's experience from a different angle. It takes into account if the analyst has given any EPS forecasts at the time of revising his recommendation for the company in question. If the analyst has not yet made any earnings estimates, he may be more likely to use consensus earnings estimates for his P/E calculations, for instance.

Table 5. Control variables

This table defines the control variables used in regressions in Chapter 5.

Variable	Definition
Accruals	Total accruals divided by total assets on a quarterly basis. The change in non-cash current assets minus the change in current liabilities, excluding the change in debt included in current liabilities and the change in income taxes payable minus depreciation and amortization expense, divided by average total assets
Analyst coverage	The number of analysts providing one-year earnings forecasts in prior three months (divided by 100 in regressions)
Analyst dispersion	Standard deviation across earnings forecasts in the prior three months from IBES summary detail file
Analyst experience	Natural logarithm of recommendation revision year subtracted by number of years plus one year since the analyst gave its first EPS estimate for the firm in question. Negative values are replaced by 0.
Analyst herding	Dummy that equals 1 if multiple recommendation revisions are issued at the same day for the same company
B/M	Book value of equity divided by market value of equity
Capex	Rolling sum of capital expenditure in the previous four quarters divided by the average total assets
Forecast revisions	Rolling sum of previous six months' revisions to price ratios, using mean consensus EPS forecasts for the next fiscal year
Forecast accuracy	Absolute earnings forecast error calculated as actual earnings per share minus the median forecasted EPS scaled by stock price
Idiosyncratic volatility	The standard deviation of the residuals of the Fama-French 3-factor model estimated using the daily stock returns in the past three months, specifically from day t-1 to t-63
Institutional ownership	Share of institutional ownership. Shares owned by institutes retrieved from Thomson Reuters
LTG	Most recent median consensus long-term growth forecast (divided by 100 in regressions)
P/E	Stock price divided by actual earnings from the last available fiscal year
$Return_{m-12, m-7}$	Cumulative return from month -7 to -12 (day t-127 to t-252)
$Return_{m-6, m-2}$	Cumulative return from month -2 to -6 (day t-22 to t-126)
$Return_{t-21, t-6}$	Cumulative return from day t-6 to t-21
$Return_{t-5, t-1}$	Cumulative return from day t-1 to t-5 before recommendation revision date t
Sales growth	Rolling sum of sales in the previous four quarters divided by the rolling sum of sales in the second preceding set of four quarters
Size	Natural logarithm of market value at day t-22
SUE	Standardized unexpected earnings. Unexpected earnings for the most recent reporting quarter scaled by its standard deviation over the eight preceding quarters. Unexpected earnings are EPS for the quarter t minus EPS for quarter t-4, where EPS is diluted excluding extraordinary items and adjusted for stock distributions. Most recent quarter is prior quarter before earnings announcement was made
Turnover	Average daily turnover in the previous three months divided by shares outstanding

My tests are similar to Li et al. (2016) which is why a similar control variable set is appropriate. Li et al. (2016) uses control variables that have known correlation with analyst stock recommendations. Jegadeesh et al. (2004) further discusses the most important known variables that have demonstrated ability to predict cross-sectional returns and why analyst recommendations are also correlated with these variables. The authors state that analysts may be explicitly or intuitively aware of these variables to predict future returns and thus these variables correlate with analyst recommendations in the same way they are correlated with future returns when this assumption holds.

Furthermore, control variables are not of the main interest as these are extensively studied by academics. Thus, the interpretation and discussion of results focus on the anchoring effects on the Approach dummies which give new insights. To cite the effects of few control variables, Lee and Swaninathan (2000) find that turnover has negative correlation with future returns, Lakonishok et al. (1994) find that sales growth has negative correlation to future returns, Chan et al. (2006) find accruals to have negative relationship with future returns and Beneish et al. (2001) find capital expenditures to have a negative relationship with future returns. For instance, negative correlation between turnover and future returns means that high (low) volume stocks are overvalued (undervalued). If analyst believes in the predictive power of trading volume, recommendations are more likely to lean more towards lower-volume stocks than higher-volume stocks. Table 6 shows the summary of the expected effect of the approach dummies on downgrades based on the Hypotheses introduced in Chapter 1 – Introduction.

Table 6. Summary of the expected effect of the approach dummies on downgrades

This table shows the expected effect of the approach dummies on downgrades based on the Hypotheses introduced in Chapter 1 – Introduction.

Approach dummy	Expected effect on downgrade
Approach 52-week high stock price	Positive
Approach 52-week low stock price	Negative
Approach 2-year high P/E ratio	Positive
Approach 2-year low P/E ratio	Negative

4.2 Selected valuation multiples and approach dummies

The main valuation multiple used in this study is price-to-earnings (P/E). Price-to-earnings is calculated as market capitalization divided by the median forecast of EPS before extraordinary items at day t-1 for the next fiscal year. To arrive at P/E ratio, first market capitalization needs to be calculated. Furthermore, instead of pure next fiscal year EPS estimates, I use slightly smoothed estimates to smooth the change in estimation window after the announcement of the annual results. In Figure 6 in Appendix, I provide an example case how estimates are smoothed.

Market capitalization (mcap) in Equation 2 is defined as closing price on day t-1 (prc) multiplied by shares outstanding on day t-1 (shrout). If closing price is not available, bid/ask average is used as a proxy. Furthermore, Enterprise value is also needed in order to calculate other market multiples than P/E. Enterprise value (Eq. 3), in other words EV, at day t-1 is defined as the sum of market capitalization (mcap) and net debt. Net debt is the sum of total long-term debt (dlttq), debt in current liabilities (dlcq), redeemable noncontrolling interest on balance sheet (mibq) and total preferred/preference stock capital (pstkq) less cash and short term investments (cheq). The latest publicly available quarterly accounting information on day t-1 is used for the accounting information components.

$$mcap_{j,t-1} = prc_{j,t-1} \times shrout_{j,t-1} \tag{2}$$

$$EV_{j,t-1} = mcap_{j,t-1} + dlttq_{j,q} + dlcq_{j,q} + mibq_{j,q} + pstkq_{j,q} - cheq_{j,q} \tag{3}$$

where subscript j denotes the stock j, q the latest available quarter and t-1 the day.

As mentioned, the main valuation multiple used in this thesis is P/E. Other multiples used are PEG ratio and Enterprise value based multiples of EV/EBITDA, EV/EBIT and EV/Sales. Table 7 describes the calculations behind the multiples used. However, the next fiscal year period is smoothed as shown and explained more thoroughly in Figure 6 in Appendix. In addition to the forward-looking multiples used and defined in Table 7, regressions are tested with historical-looking multiples which are based on actual measures in the last available fiscal year. EBITDA forecasts for instance are scarce in IBES database before 2002 and even after that, only a fraction of analysts have given EBITDA estimates to a fraction of companies.

Table 7. Forward-looking valuation multiples

This table shows the forward-looking valuation multiples used in the analyses.

Forward-looking valuation multiple	Definition
EV/EBITDA	Enterprise value divided by median forecast EBITDA for the next fiscal year at day t-1
EV/EBIT	Enterprise value divided by median forecast EBIT for the next fiscal year at day t-1
EV/Sales	Enterprise value divided by median forecast Sales for the next fiscal year at day t-1
P/E	Market capitalization divided by the median forecast of EPS before extraordinary items for the next fiscal year at day t-1
PEG ratio	P/E ratio divided by median annual forecast of growth in EPS before extraordinary items at day t-1

For the approach dummies, I need to set a range where the level of the selected measure is considered to be close to e.g. the 52-week high or low. In the base case, 5% band is assumed. The 5% band is chosen similarly to Li et al. (2016) who use 5% band in their main tests. For downgrades (upgrades), it means that the selected measure at day t-1 needs to be within a 5% band below (above) the 52-week high (low) of the selected measure. Robustness checks are performed with different ranges from 1% up to 30% and shown in Figures 2-5.

5. Empirical results and discussion of results

This chapter provides results of empirical tests and the results are compared to the prior literature. The first two sections provide analysis for hypotheses 1-2 while the third section tests the robustness of these results. The fourth section provides analysis for hypotheses 3-4. In the fifth section additional regressions and robustness checks are run.

5.1 Anchoring to the 52-week high stock price

In this section, I present the results of the conditional logistic regression analysis on the 52-week high phenomenon. I examine whether analysts partly anchor their views to the 52-week high stock price with similar analysis to Li et al. (2016). I also test the robustness of my results with different model specifications. Baseline regressions are run with *Approach52* dummy that equals 1 if the stock price at day t-1 is within 5% below the 52-week high stock price before the recommendation revision day t. Furthermore, I compare my results with Li et al. (2016) findings. Lastly, I run a set of regressions with different definitions of *Approach52* dummy and results are illustrated in Figure 2. The *Approach52* dummy is defined with various thresholds for the nearness of current price to the 52-week high stock price ranging from 1% to 30% below the 52-week high stock price.

Table 8 reports the regression results of the conditional logit model for the anchoring effect of 52-week high stock price on analyst recommendation downgrades. I estimate five models with different specifications, consistent to Li et al. (2016). Model 1 includes only *Approach52* dummy. Model 2 includes both *Approach52* dummy and four *Return* variables that capture the price momentum effect. Model 3 includes also earnings momentum effects with *Forecast revisions* and *SUE* variables. Model 4 includes on top of that valuation indicators of *Size*, *B/M* (Book-to-market), *Turnover* and *P/E* (Price-to-earnings) as well as fundamental indicators of *Accruals* and *Capex* (Capital expenditure) and growth indicators of *LTG* (Long-term growth forecast) and *Sales growth*. Lastly, Model 5 controls also further factors related to analyst recommendation decisions as indicated in Loh and Stulz (2011): *Idiosyncratic volatility*, *Institutional ownership*, *Analyst coverage*, *Analyst dispersion*, *Analyst experience* and *Analyst herding*. Definitions of all control variables are provided in Table 5 in Chapter 4 – Methods. Regressions also control for SIC 10 industry and year fixed effects and coefficients from logit regressions are reported as log odds ratios but interpreted in terms of odds ratios. The Wald chi-squared statistics are statistically significant at the 1% level in all five model specifications which confirms the overall significance of the regression models.

Table 8 shows the regression results that test Hypothesis 1. The approaching 52-week high dummy (*Approach52*) is significantly positive at the 1% level in all five models which means that analysts are more likely to downgrade stock recommendations with prices approaching the 52-week high. *Z*-statistics is high, ranging between 7.65 and 9.48. The coefficient of *Approach52* (log odds ratio) varies between 0.317 and 0.370. Thus, the corresponding odds ratio varies between 1.374 ($e^{0.317}$) and 1.448 ($e^{0.370}$). In terms of economic magnitude, the odds of being downgraded by analysts are 37.4% – 44.8% higher for companies with stock prices approaching the 52-week high than that for other companies.

However, it is noticeable that variables $Return_{t-21,\ t-6}$ and *Forecast revisions* are also significant at the 1% level in all of their model specifications and have many times higher coefficients. This implies that these variables are more powerful compared to *Approach52* dummy even though the *z*-statistics are substantially smaller for both of these two variables. Coefficient for $Return_{t-21,\ t-6}$ is positive and varies between 1.687 and 2.078 while coefficient for *Forecast revisions* is negative varies between -5.032 and -6.558. In addition, $Return_{m-6,\ m-2}$ and $Return_{m-12,\ m-7}$ variables are statistically significant in Models 2 and 3 but not in Models 4 and 5. Furthermore, coefficients are significantly negative whereas coefficient for $Return_{t-21,\ t-6}$ is positive. $Return_{m-6,\ m-2}$ varies between -0.141 and -0.424 while $Return_{m-12,\ m-7}$ varies between -0.034 and -0.169.

As variable $Return_{t-21,\ t-6}$ is significantly positive, it means that analysts are more likely to downgrade companies that have had recent price run-up between trading days t-21 and t-6. In Model 5, the coefficient for $Return_{t-21,\ t-6}$ is 2.078, which means that the odds ratio associated with a 10% increase in $Return_{t-21,\ t-6}$ is 1.231 ($e^{2.078\times0.1}$). As a result, the odds of being downgraded increase by 23.1% with a 10% increase in price run-up between the trading days *t-21* and *t-6* before the recommendation revision day *t*. However, all other Return variables are negative and suggest that analysts are less likely to downgrade firms with recent price run-ups in the last five trading days or in-between months *m-12* and *m-2* before the recommendation revision month *m*. Nevertheless, these results are insignificant in Model 4 with additional growth, value and fundamental indicators and in Model 5 where also analyst related factors as well as idiosyncratic volatility of the stock and institutional ownership are included. In contrast to my results, Li et al. (2016) find no statistical significance for $Return_{t-21,\, t-6}$ and the variable is not consistently positive or negative. However, Li et al. (2016) find that other *Return* variables are negative (consistent with my results) and statistically significant (inconsistent with my results). The differences in results may be partly due to different sample size where my sample has less negative cumulative returns on average and less standard deviation and companies are of much larger size in terms of market capitalization.

From other control variables, *P/E* and *Turnover* are statistically significant in Model 4 but insignificant in Model 5. Furthermore, their coefficients are close to zero. In Model 5, *Analyst herding* is statistically significant at 1% level and the coefficient is 0.269 and positive. Thus, it seems that herding increases the probability of downgrading, specifically when multiple analysts have given recommendation revisions for the same company on the same day.

Results provide evidence for Hypothesis 1 and are consistent with Li et al. (2016). Findings by Li et al. (2016) using all control variables and excluding reiterations show that odds of being downgraded by analysts are 42.6% higher for companies with stock prices approaching 52-week high than that of other companies whereas I find that they are 44.8% more likely[9]. The effect is thus consistent though slightly stronger with my sample. One reason for the difference is the sample size since Li et al. (2016) sample includes 121,158 observations while my main sample with all control variables include only 17,508 observations due to the tight requirements set for the earnings estimates (and control variables) in my analysis.

Furthermore, in my Model 5, sample mean probability of a downgrade is 52.9% that corresponds to an odds ratio of 1.121. Li et al. (2016) sample mean probability with all control variables and including reiterations is 41.3% and corresponds to an odds ratio of 0.704. Authors show that if the odds of being downgraded for a stock were equal to the sample mean, then the odds ratio of 1.327 associated with approaching the 52-week high (*Approach52*=1) implies that the odds ratio of being downgraded would increase to 0.934. That corresponds to a probability of 48.3% so that increase in downgrade probability is about 17% when stock price is

[9] Note that my sample excludes reiterations and Li et al. (2016) main sample includes reiterations where the odds of being downgraded by analysts are about 32.7% higher with all control variables.

approaching the 52-week high. In my Model 5, regression odds ratio is 1.448 which implies that the odds ratio of being downgraded would increase to 1.624. As my sample mean probability is 52.9%, the corresponding downgrade probability is 61.9% so the increase in probability is about 17% (new probability relative to the old probability) when stock price is approaching the 52-week high.

Interpretation of my results is thus very similar to Li et al. (2016) even when they have included reiterations of recommendations in regressions. The economic magnitude of anchoring bias is also comparable to incentive bias in M&A deals. For instance, Kolasinski and Kothari (2008) find that an analyst is more likely to upgrade the recommendation within the next 90 days in M&A transaction in all-cash deals and that acquirer affiliation increases the odds of a recommendation upgrade of the acquirer by a factor of more than 1.5.

In Figure 2, results of additional set of regressions with all control variables (as indicated in Model 5 of Table 8) but with different definitions of *Approach52* dummy are illustrated. In Table 8, baseline regressions are run with *Approach52* dummy that equals 1 if the stock price at day t-1 is within 5% threshold below the 52-week high stock price before the recommendation revision day t. In Table 8, the *Approach52* dummy is defined with various thresholds for the nearness of price at day t-1 to the 52-week high stock price from 1% up to 30% below the 52-week high stock price. The figure shows that similar log odds ratios are obtained with threshold of between ca. 5% and 10% and *Approach52* dummy is significant at 1% level until ca. 19% threshold. The results from these regressions give further support to my Hypothesis 1 that analysts partly anchor their recommendation revisions to 52-week high stock price.

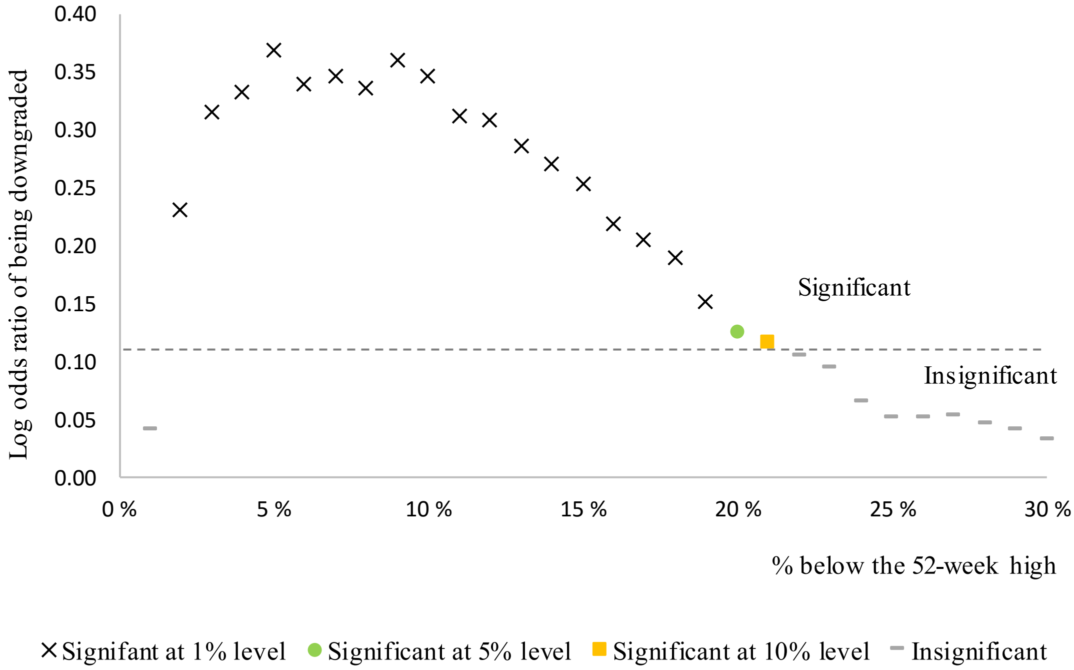
Table 8. The effect of 52-week high stock price on analyst recommendation downgrade

This table shows the predictability of approaching 52-week high stock price on recommendation downgrade. Results are based on conditional logit regression: $Downgrade_{j,t} = \beta_0 + \beta_1 Approach52_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. Dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach52* is dummy that equals 1 if stock price at day t-1 is within 5% below the 52-week high. Vector X includes a set of control variables (See Table 5 for full definitions). *Return* variables denote for cumulative return between days t or months m, where $Return_{t-5,\ t-1}$ is from day t-5 to t-1, $Return_{t-21,\ t-6}$ is from day t-21 to t-6, $Return_{m-6,\ m-2}$ is from month -6 to month -2, and $Return_{m-12,\ m-7}$ is from month -12 to month -7. *Forecast revisions* is rolling sum of previous six months' EPS revisions to price ratio. *SUE* is the standardized unexpected earnings. *Size* is the natural logarithm of market value at day t-22. *B/M* is book value of equity divided by market value of equity. *P/E* is price-to-earnings ratio based on actual earnings in the last available fiscal year. *Turnover* is average daily turnover in the previous three months divided by shares outstanding. *Accruals* are total accruals divided by average total assets on a quarterly basis. *Capex* is rolling sum of capital expenditure in the previous four quarters divided by average total assets. *Sales growth* is the rolling sum of sales in the previous four quarters divided by rolling sum of sales in the second preceding set of four quarters. *LTG* is median consensus long-term growth forecast. *Idiosyncratic volatility* is the standard deviation of the residuals of FF3-factor model. *Institutional ownership* is the ownership of institutes in percentages. *Analyst coverage* is number of analysts providing one-year earnings forecasts in prior three months. *Analyst dispersion* is the standard deviation across earnings forecasts in the prior three months. *Analyst experience* is the natural logarithm of recommendation revision year minus number of years plus one (or 0 if negative) since the analyst gave its first EPS estimate for the firm in question. All regressions control for year and SIC 10 industry fixed effects. Coefficients are reported as log odds ratios and z-statistics are based on two-way clustered standard errors by firm and year. Sig. denotes for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

Cond. logit model	(1)			(2)			(3)			(4)			(5)		
Downgrade	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach52	0.321	***	9.48	0.315	***	8.67	0.317	***	8.55	0.355	***	7.65	0.370	***	8.17
$Return_{t-5,\ t-1}$				-0.208		-0.92	-0.010		-0.04	-0.169		-0.42	-0.093		-0.18
$Return_{t-21,\ t-6}$				1.687	***	11.29	1.841	***	11.69	2.007	***	6.04	2.078	***	3.96
$Return_{m-6,\ m-2}$				-0.424	***	-7.94	-0.269	***	-4.58	-0.160		-1.45	-0.141		-1.31
$Return_{m-12,\ m-7}$				-0.169	***	-3.33	-0.101	*	-1.88	-0.034		-0.49	-0.066		-0.63
Forecast revisions							-6.558	***	-7.25	-5.461	***	-4.64	-5.032	***	-4.31
SUE							0.014		1.29	-0.002		-0.16	-0.006		-0.40
Size										-0.006		-0.03	0.040		0.11
B/M										0.327		0.65	0.330		0.56
P/E										-0.001	**	-2.11	-0.001		-1.36
Turnover										0.008	***	2.61	0.003		1.13
Accruals										0.342		0.69	0.260		0.64
Capex										-0.061		-0.12	0.057		0.05
Sales growth										0.309		0.60	0.270		0.58
LTG										0.003		0.24	0.000		-0.01
Idiosyncratic volatility													9.148		0.56
Institutional ownership													0.175		0.42
Analyst coverage													-0.632		-0.17
Analyst dispersion													-0.183		-0.51
Analyst experience													-0.004		-0.90
Analyst herding													0.269	***	3.35
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes		
Observations	35,258			30,001			28,562			17,684			17,508		
Wald chi^2	89.81			296.86			324.74			274.49			309.90		
Pseudo R^2	0.002			0.010			0.012			0.015			0.018		

Figure 2. The log odds ratio of being downgraded with nearness to the 52-week high

Figure 2 shows the log odds ratio of being downgraded with nearness to the 52-week high stock price. Approaching 52-week high dummy equals 1 if the stock price at trading day t-1 is within x% below the 52-week high stock price, i.e. (1-x) × 52-week high stock price < stock price at day t-1 < 52-week high stock price. Results are based on conditional logit regression with all control variables defined in Table 5. The logit regression is: $Downgrade_{j,t} = \beta_0 + \beta_1 Approach52_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. Plotted coefficients are reported as log odds ratios. See Table 8 for more information on regressions with Approach52 dummy that has a threshold of 5% below the 52-week high.



5.2 Anchoring to the 52-week low stock price

In this section, I present the results of the conditional logistic regression analysis on the 52-week low phenomenon. I examine whether analysts partly anchor their views on the 52-week low stock price with similar analysis to Li et al. (2016). I also test robustness of my results with different model specifications. Baseline regressions are identical to Section 5.1 but instead of *Approach52* dummy they are run with *Approach52low* dummy that equals 1 if the stock price at day t-1 is within 5% above the 52-week low stock price before the recommendation revision day t. Furthermore, I compare my results with Section 5.1 findings and Li et al. (2016) findings. Lastly, I run a set of regressions with different definitions of *Approach52low* dummy and results are illustrated in Figure 3. The *Approach52low* dummy is defined with various thresholds for the nearness of price at day t-1 to the 52-week low stock price ranging from 1% to 30% above the 52-week low stock price.

Table 9 reports the regression results of the conditional logit model for the anchoring effect of 52-week low stock price on analyst recommendation downgrades. The regression results test Hypothesis 2 which states that analysts would be less likely to downgrade the stock when stock prices approach the 52-week low. Contrary to Hypothesis 2, the coefficient is positive and thus to the opposite direction than was predicted. The Wald chi-squared statistics are statistically significant at the 1% level in all five model specifications confirming the overall significance of the regression models. The approaching 52-week low dummy (*Approach52low*) is statistically significant and positive at the 1% level in all five models which means that analysts are more likely to downgrade stock recommendations when stock prices are approaching the 52-week low. *Z*-statistics is high ranging from 4.72 to 6.11. Furthermore, the coefficient of *Approach52low* varies between 0.244 and 0.372, indicating very similar effect to the 52-week high phenomenon. The corresponding odds ratio varies between 1.276 ($e^{0.244}$) and 1.451 ($e^{0.372}$). Thus, the odds of being downgraded by analysts are 27.6% – 45.1% higher for companies with stock prices approaching the 52-week low than that for other companies. In the case of approaching 52-week high stock price (in Section 5.1), the range is 37.4% – 44.8%.

When it comes to control variables, results are in line with Section 5.1 results. The statistically significant variables at the 1% level are the same in Model 5 as in Section 5.1. The coefficient for *Return* $_{t-21,\, t-6}$ and *Analyst herding* are positive and for *Forecast revisions* is negative. Also coefficients for other control variables are mostly in similar magnitude to the Section 5.1 results. Results do not support Hypothesis 2 but are partly consistent with Li et al. (2016). Li et al. (2016) find that the coefficient for *Approach52low* is slightly positive (0.033) but they do not find any statistically significant results while my results are statistically significant. One reason for Li et al. (2016) not finding significant results may be that they included reiterations in the regressions which may weaken the effect as it seems to be the case in their results of the 52-week high phenomenon (The effect is stronger without reiterations as mentioned in Section 5.1). Another difference is the sample size as my sample size is smaller with larger companies and the companies have had less negative cumulative returns before the recommendation revision.

Results provide evidence against Hypothesis 2 and lead to rejection of Hypothesis 2. 52-week low seems to affect similarly to 52-week high phenomenon. The increase in downgrade probability is about 17% in case of approaching the 52-week low stock price and also about 17% when approaching the 52-week high stock price[10]. Figure 3 shows further support for the effect. It shows the log odds ratio from the results of additional set of regressions with all control variables (as indicated in Model 5 of Table 9). Regressions are run with different definitions of *Approach52low* dummy. The *Approach52low* dummy is defined with various thresholds for the nearness of price at day t-1 to the 52-week low stock price ranging from 1% up to 30% above the 52-week low stock price. The figure shows that similar log odds ratios are obtained with threshold of between ca. 5% and 8% and *Approach52low* dummy is significant at the 1% level until ca. 17% threshold. Analysts thus seem to partly anchor their recommendations to both 52-week high and 52-week low stock prices and as a result downgrades are more likely in both reference points.

[10] Based on Model 5 coefficients in both main regressions (Table 8 and Table 9).

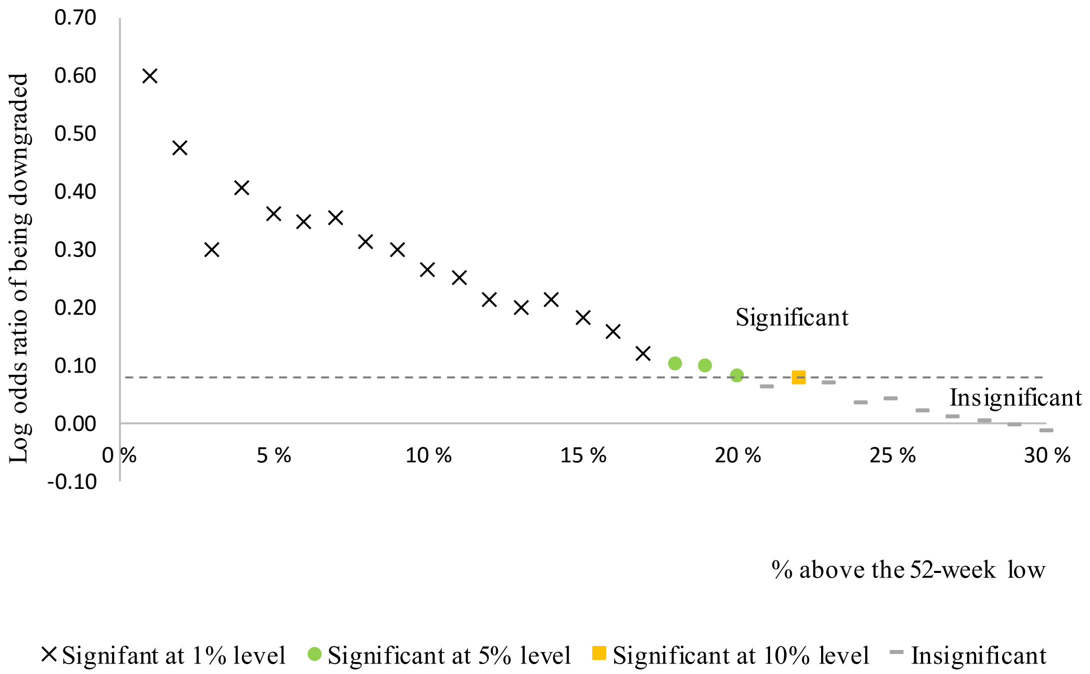
Table 9. The effect of 52-week low stock price on analyst recommendation downgrade

This table shows the predictability of approaching 52-week low stock price on recommendation downgrade. Results are based on conditional logit regression: $Downgrade_{j,t} = \beta_0 + \beta_1 Approach52low_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. Dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach52low* is dummy that equals 1 if stock price at day t-1 is within 5% above the 52-week low. Vector X includes a set of control variables (See Table 5 for full definitions). *Return* variables denote for cumulative return between days t or months m, where $Return_{t-5,\ t-1}$ is from day t-5 to t-1, $Return_{t-21,\ t-6}$ is from day t-21 to t-6, $Return_{m-6,\ m-2}$ is from month -6 to month -2, and $Return_{m-12,\ m-7}$ is from month -12 to month -7. *Forecast revisions* is rolling sum of previous six months' EPS revisions to price ratio. *SUE* is the standardized unexpected earnings. *Size* is the natural logarithm of market value at day t-22. *B/M* is book value of equity divided by market value of equity. *P/E* is price-to-earnings ratio based on actual earnings in the last available fiscal year. *Turnover* is average daily turnover in the previous three months divided by shares outstanding. *Accruals* are total accruals divided by average total assets on a quarterly basis. *Capex* is rolling sum of capital expenditure in the previous four quarters divided by average total assets. *Sales growth* is the rolling sum of sales in the previous four quarters divided by rolling sum of sales in the second preceding set of four quarters. *LTG* is median consensus long-term growth forecast. *Idiosyncratic volatility* is the standard deviation of the residuals of FF3-factor model. *Institutional ownership* is the ownership of institutes in percentages. *Analyst coverage* is number of analysts providing one-year earnings forecasts in prior three months. *Analyst dispersion* is the standard deviation across earnings forecasts in the prior three months. *Analyst experience* is the natural logarithm of recommendation revision year minus number of years plus one (or 0 if negative) since the analyst gave its first EPS estimate for the firm in question. All regressions control for year and SIC 10 industry fixed effects. Coefficients are reported as log odds ratios and z-statistics are based on two-way clustered standard errors by firm and year. Sig. denotes for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

Cond. logit model	(1)			(2)			(3)			(4)			(5)		
Downgrade	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach52low	0.244	***	4.72	0.335	***	6.11	0.323	***	5.81	0.372	***	5.31	0.362	***	5.16
Return $_{t-5,\ t-1}$				0.236		1.05	0.438	*	1.86	0.321		0.81	0.404		0.77
Return $_{t-21,\ t-6}$				2.031	***	13.43	2.196	***	13.74	2.397	***	7.37	2.476	***	4.70
Return $_{m-6,\ m-2}$				-0.271	***	-5.05	-0.115	*	-1.94	0.003		0.03	0.024		0.23
Return $_{m-12,\ m-7}$				-0.125	**	-2.43	-0.057		-1.05	0.015		0.21	-0.015		-0.14
Forecast revisions							-6.442	***	-7.15	-5.387	***	-4.58	-5.064	***	-4.33
SUE							0.013		1.22	-0.003		-0.23	-0.007		-0.44
Size										-0.001		-0.01	0.045		0.13
B/M										0.317		0.63	0.323		0.55
P/E										-0.001	**	-2.07	-0.001		-1.35
Turnover										0.007	**	2.27	0.003		1.05
Accruals										0.265		0.53	0.183		0.45
Capex										-0.106		-0.21	0.023		0.02
Sales growth										0.310		0.60	0.275		0.59
LTG										0.002		0.16	-0.001		-0.07
Idiosyncratic volatility													7.876		0.48
Institutional ownership													0.167		0.40
Analyst coverage													-0.679		-0.19
Analyst dispersion													-0.199		-0.56
Analyst experience													-0.005		-0.97
Analyst herding													0.272	***	3.41
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes		
Observations	35,258			30,001			28,562			17,684			17,508		
Wald chi^2	22.31			248.90			273.91			234.36			263.89		
Pseudo R^2	0.001			0.009			0.011			0.014			0.016		

Figure 3. The log odds ratio of being downgraded with nearness to the 52-week low

Figure 3 shows the log odds ratio of being downgraded with nearness to the 52-week low stock price. Approaching 52-week low dummy equals 1 if the stock price at trading day t-1 is within x% above the 52-week low stock price, i.e. 52-week low stock price < stock price at day t-1 < (1+x) × 52-week low stock price. Results are based on conditional logit regression with all control variables defined in Table 5. The logit regression is: $Downgrade_{j,t} = \beta_0 + \beta_1 Approach52low_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. Plotted coefficients are reported as log odds ratios. See Table 9 for more information on regressions with *Approach52low* dummy that has a threshold of 5% above the 52-week low.



5.3 Robustness checks for the 52-week high and low phenomenon

5.3.1 Approaching 52-week high and low stock price

As a robustness check for the results in Sections 5.1 and 5.2, I run conditional logistic regression including the approach dummies of both 52-week high and 52-low stock price. Results are consistent with results in Sections 5.1 and 5.2 and both approach dummies are significant at 1% level in all five model specifications. Results are provided in Table 10. Furthermore, I run regressions with alternative methods and measures of approaching 52-week high and low stock prices. In Table 11, I run similar regressions to the main tests with OLS and probit models. I also test consistency of results with alternative measures to 52-week high and low by using the price relative to 52-week high (low) and square root of price to 52-week high (low). The results are run with OLS, probit and logit models and are provided in Table 11 as well. Results give further support for the statistical significance of the measures.

Table 10 reports the regression results of the conditional logit model for the anchoring effects of the 52-week high and low stock prices on analyst recommendation downgrades. The Wald chi-squared statistics are statistically significant at the 1% level in all five model specifications confirming the overall significance of the regression models. The coefficients for *Approach52* are similar to regression results in Table 8 and the coefficients for *Approach52low* are similar to Table 9. Furthermore, both dummies have similar, positive effect on recommendation downgrades[11]. In Model 5, the coefficient for *Approach52* is 0.379 and for *Approach52low* is 0.383. This means that the odds of being downgraded by analysts are ca. 46.1% – 46.7% higher for companies with stock prices approaching the 52-week high or low stock price than that for other companies.

Nevertheless, it is noticeable that from control variables *Return* $_{t-21,\ t-6}$ and *Forecast revisions* seem to be more important compared to *Approach* dummies as these dummies have higher coefficients and they are statistically significant at the 1% level. However, this is partly in line with Li et al. (2016) as their results also indicate that two *Return* variables are greater compared to *Approach52* dummy but they also find that the coefficients for *Turnover and Idiosyncratic volatility* are high. In my regression, the coefficient for idiosyncratic volatility is also extremely high but I find it statistically insignificant.

[11] Note that these *Approach* dummies are not coinciding for any recommendation revision, i.e. that both dummies would have the value of 1 at the same time.

Table 11 reports the regressions results with different regression models and different measures for approach dummies. The logit and probit regressions have *Downgrade* as the dependent variable whereas in OLS regression *Recommendation revision* is the dependent variable. Models 1 and 2 confirm the significance of *Approach52* and *Approach52low* dummies as both OLS and probit regressions yield statistically significant results at the 1% level. Coefficients are also to the same direction and of similar kind of magnitude. Furthermore, $Return_{t-21,\, t-6}$ as well as *Forecast revisions* and *Analyst herding* are statistically significant at the 1% level, supporting the results in the main tests of Sections 5.1 and 5.2. In addition, many other control variables have statistical significance in these econometric models which is in line with Li et al. (2016) results.

Table 11 also reports regressions with an alternative method to measure the nearness to the 52-week high and low stock price. *Price to 52 high* and *Price to 52 low* and their square roots measure how near the price is relative to the 52-week high and low. Models 3-5 (Columns 4-6) show regression results of OLS, probit and logit regressions with these measures, supporting the results from the main tests that analysts partly anchor their recommendation revisions to both 52-week high and 52-week low stock prices.

Table 10. The effect of 52-week high and low on analyst recommendation downgrade

This table shows the predictability of approaching 52-week high and low stock price on recommendation downgrade. The cond. logit regression is: $Downgrade_{j,t} = \beta_0 + \beta_1 Approach52_{j,t-1} + \beta_2 Approach52low_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. Dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach52* (*Approach52low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low). Vector X includes a set of control variables (See Table 5 for full definitions). *Return* variables denote for cumulative return between days t or months m, where $Return_{t-5,\ t-1}$ is from day t-5 to t-1, $Return_{t-21,\ t-6}$ is from day t-21 to t-6, $Return_{m-6,\ m-2}$ is from month -6 to month -2, and $Return_{m-12,\ m-7}$ is from month -12 to month -7. *Forecast revisions* is rolling sum of previous six months' EPS revisions to price ratio. *SUE* is the standardized unexpected earnings. *Size* is the natural logarithm of market value at day t-22. *B/M* is book value of equity divided by market value of equity. *P/E* is price-to-earnings ratio based on actual earnings in the last available fiscal year. *Turnover* is average daily turnover in the previous three months divided by shares outstanding. *Accruals* are total accruals divided by average total assets on a quarterly basis. *Capex* is rolling sum of capital expenditure in the previous four quarters divided by average total assets. *Sales growth* is the rolling sum of sales in the previous four quarters divided by rolling sum of sales in the second preceding set of four quarters. *LTG* is median consensus long-term growth forecast. *Idiosyncratic volatility* is the standard deviation of the residuals of FF3-factor model. *Institutional ownership* is the ownership of institutes in percentages. *Analyst coverage* is number of analysts providing one-year earnings forecasts in prior three months. *Analyst dispersion* is the standard deviation across earnings forecasts in the prior three months. *Analyst experience* is the natural logarithm of recommendation revision year minus number of years plus one (or 0 if negative) since the analyst gave its first EPS estimate for the firm in question. All regressions control for year and SIC 10 industry fixed effects. Coefficients are reported as log odds ratios and z-statistics are based on two-way clustered standard errors by firm and year. Sig. denotes for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

Cond. logit model	(1)			(2)			(3)			(4)			(5)		
Downgrade	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach52	0.339	***	9.90	0.323	***	8.87	0.326	***	8.75	0.364	***	7.84	0.379	***	8.37
Approach52low	0.295	***	5.64	0.353	***	6.42	0.342	***	6.12	0.391	***	5.58	0.383	***	5.46
Return $_{t-5,\ t-1}$				-0.031		-0.14	0.166		0.70	0.020		0.05	0.094		0.18
Return $_{t-21,\ t-6}$				1.813	***	11.99	1.966	***	12.34	2.148	***	6.46	2.217	***	4.21
Return $_{m-6,\ m-2}$				-0.372	***	-6.86	-0.220	***	-3.70	-0.111		-1.00	-0.091		-0.84
Return $_{m-12,\ m-7}$				-0.146	***	-2.85	-0.079		-1.46	-0.012		-0.17	-0.045		-0.43
Forecast revisions							-6.435	***	-7.15	-5.225	***	-4.43	-4.790	***	-4.09
SUE							0.015		1.32	-0.002		-0.12	-0.006		-0.38
Size										-0.007		-0.05	0.038		0.11
B/M										0.325		0.65	0.326		0.55
P/E										-0.001	**	-2.09	-0.001		-1.34
Turnover										0.008	***	2.63	0.003		1.08
Accruals										0.333		0.68	0.251		0.62
Capex										-0.045		-0.09	0.066		0.06
Sales growth										0.316		0.61	0.276		0.59
LTG										0.003		0.25	0.000		0.00
Idiosyncratic volatility													9.410		0.58
Institutional ownership													0.174		0.42
Analyst coverage													-0.634		-0.18
Analyst dispersion													-0.170		-0.48
Analyst experience													-0.004		-0.90
Analyst herding													0.275	***	3.42
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes		
Observations	35,258			30,001			28,562			17,684			17,508		
Wald chi^2	114.84			334.25			358.24			306.04			342.71		
Pseudo R^2	0.003			0.011			0.013			0.0169			0.019		

Table 11. Alternative methods and measures of approaching 52-week high and low

This table reports robustness tests by different methods including OLS, probit and logit models. Logit and probit regression are run as follows: $Downgrade_{j,t} = \beta_0 + \beta_1 Approach52_{j,t-1} + \beta_2 Approach52low_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. OLS regression is run as follows: $Revision_{j,t} = \beta_0 + \beta_1 Approach52_{j,t-1} + \beta_2 Approach52low_{j,t-1} + \delta' X_j + Firm\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. Dependent variable in probit and logit regressions is *Downgrade* which is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. Dependent variable in OLS regressions is *Revision* which is the recommendation revision which gets values between -4 to 4 where positive values indicate upgrades and negative values downgrades. *Approach52* is dummy that equals 1 if stock price at day t-1 is within 5% below the 52-week high. *Approach52low* is dummy that equals 1 if stock price at day t-1 is within 5% above the 52-week low. *Price to 52 high* and *Price to 52 low* are alternative measures for measuring nearness to 52-week high stock price and 52-week low price, respectively. *Sqrt price to 52 high* and *Sqrt price to 52 low* are square roots of the aforementioned prices relative to 52-week high and low and capture the non-linear relationship between recommendation revision and price ratios. Vector X includes a set of control variables with definitions found in Table 5. OLS regressions control for firm and year fixed effects. Probit and logit regressions control for year and SIC 10 industry fixed effects. Coefficients are reported as log odds ratios in probit and logit regressions and z-statistics (or t-statistics in OLS) are based on two-way clustered standard errors by firm and year. Sig. denotes for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

Model	(1)			(2)			(3)			(4)			(5)		
	OLS (Revision)			Probit (Downgrade)			OLS (Revision)			Probit (Downgrade)			Logit (Downgrade)		
(Dependent variable)	Coef.	Sig.	t-stat	Coef.	Sig.	z-stat	Coef.	Sig.	t-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach52	-0.248	***	-7.30	0.240	***	7.49									
Approach52low	-0.263	***	-4.97	0.241	***	3.97									
Price to 52 high							-3.397	***	-4.00	4.324	***	4.94	7.391	***	5.02
Sqrt price to 52 high							8.151	***	5.72	-9.527	***	-6.51	-16.186	***	-6.48
Price to 52 low							-1.409	***	-6.87	1.290	***	8.94	2.099	***	8.49
Sqrt price to 52 low							5.704	***	9.72	-5.448	***	-11.99	-8.887	***	-11.34
$Return_{t-5,\ t-1}$	-0.473	**	-2.11	0.043		0.09	-2.632	***	-10.48	2.267	***	4.54	3.722	***	4.49
$Return_{t-21,\ t-6}$	-1.842	***	-12.85	1.335	***	7.95	-3.636	***	-21.89	3.290	***	12.83	5.423	***	12.42
$Return_{m-6,\ m-2}$	-0.036		-0.63	-0.052		-1.11	-1.298	***	-13.50	1.240	***	12.85	2.057	***	12.06
$Return_{m-12,\ m-7}$	-0.002		-0.04	-0.029		-0.72	-0.570	***	-9.20	0.556	***	6.99	0.925	***	6.82
Forecast revisions	2.364	***	3.20	-3.257	***	-4.35	1.583	**	2.05	-2.088	**	-2.30	-3.576	**	-2.37
SUE	0.001		0.10	-0.002		-0.73	0.004		0.34	-0.004		-1.13	-0.007		-1.17
Size	-0.184	***	-5.05	0.019	**	2.14	-0.091	**	-2.47	-0.003		-0.32	-0.004		-0.25
B/M	-0.700	***	-8.43	0.182	***	4.7	-0.340	***	-4.08	0.049		1.24	0.083		1.27
P/E	0.002	***	2.84	-0.001	***	-3.14	0.001		1.12	0.000		-0.87	-0.001		-0.93
Turnover	-0.003		-1.15	0.001		1.21	0.001		0.24	-0.002		-1.30	-0.003		-1.25
Accruals	-0.123		-0.47	0.108		1.17	0.153		0.59	-0.056		-0.63	-0.093		-0.63
Capex	-0.671	*	-1.67	0.074		0.38	-0.340		-0.86	0.032		0.15	0.044		0.13
Sales growth	-0.474	***	-5.85	0.212	***	3.48	-0.351	***	-4.20	0.167	**	2.38	0.271	**	2.46
LTG	0.004		1.35	-0.001		-0.69	0.003		1.04	0.000		-0.22	0.000		-0.17
Idiosyncratic volatility	-7.684	***	-3.80	5.988	***	5.22	1.299		0.57	-1.424		-0.70	-2.406		-0.71
Institutional ownership	-0.005		-0.05	0.115	***	3.02	-0.046		-0.45	0.113	**	2.30	0.185	**	2.38
Analyst coverage	-0.151		-0.47	-0.327	**	-2.26	-0.265		-0.83	-0.143		-0.97	-0.235		-0.99
Analyst dispersion	0.207	*	1.94	-0.084	*	-1.91	0.121		1.11	-0.060		-1.12	-0.101		-1.18
Analyst experience	0.005	**	2.09	-0.003		-1.37	0.005	**	2.31	-0.003		-1.47	-0.006		-1.48
Analyst herding	-0.214	***	-4.39	0.169	***	8.46	-0.156	***	-3.38	0.130	***	5.28	0.202	***	5.17
Intercept	4.735	***	5.84	-0.545	**	-2.49	-7.013	***	-5.92	9.723	***	14.19	16.135	***	13.45
Firm fixed effects	Yes			No			Yes			No			No		
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	No			Yes			No			Yes			Yes		
Observations	17,537			17,537			16,957			16,957			16,957		
Adjusted R^2/Pseudo R^2	0.024			0.023			0.042			0.040			0.040		

5.3.2 Horse-race regression between the 52-week high/low stock price and target prices

To check whether the 52-week high and low phenomena are dominant factors to drive recommendation revisions instead of target prices set by the same analyst who revises the recommendation, I run a horse-race regression between the 52-week high/low stock price and target prices. Birru (2015) finds that analysts are anchoring to target prices near the 52-week high stock prices and that analysts' target price forecasts are more pessimistic for stocks near the 52-week high than for other stocks. However, Li et al. (2015) find that anchoring to the 52-week high stock price is the dominant factor and find no statistical significance for the target prices in horse race regressions with all control variables.

In Table 12, Panel A reports horse-race regressions between the 52-week high stock price and the target prices with and without all control variables. I create dummies for target prices so that *Target price 5%* (*Target price 10%*) is a dummy that equals 1 if stock price at day t-1 is within 5% (10%) below the target price issued by the same analyst who revises the recommendation. Panel A shows that without control variables *Target price 5%* is significant at the 5% level and *Target price 10%* at the 10% level. When regressions include all control variables, *Target price 10%* loses significance but *Target price 5%* stays significant at the 10% level. Interpretation of result is consistent with Birru (2015) as the coefficient is positive and thus analysts are more likely to downgrade the stocks near the target prices. As target price has some predictability on recommendation downgrades, I include it in additional control variables in further regressions. Nonetheless, it seems that *Approach52* dummy is more powerful dummy than the *Target price 5%*.

In Table 12, Panel B reports horse-race regressions between the 52-week low stock price and the target prices with and without all control variables. I create dummies for target prices so that *Target price 5% low* (*Target price 10% low*) is a dummy that equals 1 if stock price at day t-1 is within 5% (10%) above the target price issued by the same analyst who revises the recommendation. Panel B shows that with all control variables, target price dummies lose significance and thus these variables have no predictability on recommendation downgrades. The Wald chi-squared statistics are statistically significant at the 1% level in all model specifications both in Panel A and Panel B, confirming the overall significance of the regression models. Table 13 shows the regression results from the conditional logistic regression including both Approach dummies and Target price 5% dummy with five model specifications. Results from these regressions support the main test results.

Table 12. Horse race between the 52-week high/low and target price

This table shows horse-race regression between the 52-week high stock price and target price in Panel A and horse-race regression between the 52-week low stock price and target price in Panel B. Conditional logit regression is: $Downgrade_{j,t} = \beta_0 + \beta_1 Approach52_{j,t-1} + \beta_2 Target\ price\ dummy_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. Dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. In Panel A, *Target price 5%* (*Target price 10%*) is a dummy that equals 1 if stock price at day t-1 is within 5% (10%) below the target price issued by the same analyst who revises the recommendation. In Panel B, *Target price 5% low* (*Target price 10% low*) is a dummy that equals 1 if stock price at day t-1 is within 5% (10%) above the target price issued by the same analyst who revises the recommendation. Vector X includes a set of control variables with definitions found in Table 5. All regressions control for year and SIC 10 industry fixed effects. Control variables are added when specified. Coefficients are reported as log odds ratios and z-statistics are based on two-way clustered standard errors by firm and year. Sig. denotes for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

Panel A: Horse race between the 52-week high and target price

Cond. logit model	(1)			(2)			(3)			(4)		
Downgrade	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach52	0.310	***	9.20	0.309	***	9.20	0.360	***	7.86	0.366	***	7.79
Target price 5%	0.112	**	2.45				0.143	*	1.79			
Target price 10%				0.060	*	1.71				0.048		0.69
Controls	No			No			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes		
Observations	35,258			35,258			17,508			17,508		
Wald chi^2	92.19			89.88			313.77			309.85		
Pseudo R^2	0.002			0.002			0.018			0.018		

Panel A: Horse race between the 52-week low and target price

Cond. logit model	(1)			(2)			(3)			(4)		
Downgrade	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach52low	0.253	***	4.89	0.247	***	4.77	0.360	***	5.14	0.361	***	5.15
Target price 5% low	0.214	***	3.87				0.194		1.55			
Target price 10% low				0.120	*	1.67				0.072		0.57
Controls	No			No			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes		
Observations	35,258			35,258			17,508			17,508		
Wald chi^2	36.36			24.74			270.20			264.38		
Pseudo R^2	0.001			0.001			0.016			0.016		

Table 13. The effect of 52-week high/low and target price on recommendation downgrade

This table shows the predictability of approaching the 52-week high and the 52-week low stock price as well as approaching the target price on recommendation downgrade. The conditional (fixed effects) logit regression is: $Downgrade_{j,t} = \beta_0 + \beta_1 Approach52_{j,t-1} + \beta_2 Approach52low_{j,t-1} + \beta_3 Target_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. Dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach52* (*Approach52low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low). *Target* is a dummy that equals 1 if stock price at day t-1 is within 5% below the target price issued by the same analyst who revises the recommendation. Vector X includes a set of control variables with definitions found in Table 5. All regressions control for year and SIC 10 industry fixed effects. Coefficients are reported as log odds ratios and z-statistics are based on two-way clustered standard errors by firm and year. Sig. denotes for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

Cond. logit model	(1)			(2)			(3)			(4)			(5)		
Downgrade	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach52	0.328	***	9.62	0.316	***	8.71	0.320	***	8.63	0.355	***	7.50	0.369	***	8.06
Approach52low	0.300	***	5.73	0.355	***	6.45	0.343	***	6.14	0.393	***	5.61	0.386	***	5.49
Target	0.122	***	2.66	0.102	**	2.09	0.081		1.63	0.136	*	1.88	0.148	*	1.87
Return $_{t-5, t-1}$				-0.057		-0.25	0.144		0.61	-0.013		-0.03	0.058		0.11
Return $_{t-21, t-6}$				1.791	***	11.83	1.948	***	12.22	2.118	***	6.50	2.185	***	4.23
Return $_{m-6, m-2}$				-0.376	***	-6.93	-0.225	***	-3.78	-0.118		-1.07	-0.099		-0.93
Return $_{m-12, m-7}$				-0.145	***	-2.82	-0.079		-1.45	-0.011		-0.16	-0.044		-0.43
Forecast revisions							-6.396	***	-7.13	-5.141	***	-4.37	-4.692	***	-4.02
SUE							0.015		1.33	-0.002		-0.13	-0.006		-0.39
Size										-0.007		-0.04	0.039		0.11
B/M										0.331		0.66	0.332		0.56
P/E										-0.001	**	-2.10	-0.001		-1.35
Turnover										0.008	***	2.65	0.003		1.08
Accruals										0.329		0.67	0.248		0.62
Capex										-0.042		-0.08	0.070		0.06
Sales growth										0.315		0.61	0.274		0.59
LTG										0.003		0.28	0.000		0.03
Idiosyncratic volatility													9.530		0.58
Institutional ownership													0.178		0.43
Analyst coverage													-0.636		-0.18
Analyst dispersion													-0.168		-0.47
Analyst experience													-0.004		-0.89
Analyst herding													0.277	***	3.47
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes		
Observations	35,258			30,001			28,562			17,684			17,508		
Wald chi^2	117.39			335.81			358.91			310.07			347.09		
Pseudo R^2	0.003			0.011			0.013			0.017			0.019		

5.4 Anchoring to P/E ratios and other valuation multiples

This section first tests whether anchoring to high and low P/E ratios is found. Regressions are performed with time periods of 1 year, 2 years, 3 years, 5 years and 10 years. It seems that only 2-year time period shows statistically significant results. Figure 4 and Figure 5 illustrate the results of anchoring to the 2-year high and low P/E ratios with different definitions of *Approach* dummies. Approach dummies are defined with different thresholds for the nearness of the forward-looking P/E at day t-1 before recommendation revision day t to the 2-year high (low) P/E ratio from 1% up to 30% below (above) the 2-year high (low) P/E. Lastly in this section, correlations with different Approach dummies are compared with each other including also Enterprise value multiples. Furthermore, a regression is run with all control variables and *Approach* dummies of the 52-week high and low stock prices as well as the 2-year high and low P/E ratios and target price. A regression is also run with adding two interaction terms: with 52-week high (low) stock price and 2-year high (low) stock price. Section 5.5 includes robustness checks for the results in this section.

Table 14 shows the effect of high and low P/E ratios on recommendation downgrades. Panel A tests the effects of high P/E on downgrades whereas Panel B tests the effects of low P/E on downgrades. All regressions include control variables and control for year and SIC 10 industry fixed effects. Furthermore, regressions are tested with additional set of control variables, including dummies *Approach52*, *Target* and *Appraoch52low*, which are seen to have predictability on downgrades in Sections 5.1-5.3. *Approach52* (*Approach52low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low) stock price at day t-1. *Target* is a dummy that equals 1 if the target price is within 5% below the target price issued by the same analyst who revises the recommendation. The Wald chi-squared statistics are statistically significant at the 1% level in all model specifications both in Panel A and Panel B, confirming the overall significance of the regression models.

Panel A in Table 14 shows that neither 5-year nor 10-year *Approach high P/E* dummy is significant with or without additional control variables. Instead, *Approach 1-year*, *2-year* and *3-year high P/E* dummies without additional control variables show some statistical significance on recommendation downgrade. Both *Approach 1-year* and *2-year high P/E* dummies are statistically significant at the 1% level, having positive coefficients of 0.202 and 0.282, respectively. *Approach 3-year year high P/E* dummy has a positive coefficient of 0.178 and is only statistically significant at the 10% level. Nonetheless, when additional controls are included, only *Approach 2-year high P/E* shows statistical significance, at the 10% level. Thus it seems that from the various time periods, the approaching the 2-year high P/E ratio is the most important one. Furthermore, the coefficient is positive, thus the analyst is more likely to downgrade the recommendation when the forward-looking P/E approaches the 2-year high P/E, supporting the Hypothesis 3.

Panel B in Table 14 shows that only the 2-year time period yields statistically significant results for the *Approach 2-year* dummy, similarly to results in Panel A. *Approach 2-year low P/E* dummy is statistically significant at the 10% level, having a coefficient of 0.179 when additional control variables are included in the regression. The coefficient is positive, indicating that analysts are more likely to downgrade the recommendation when the forward-looking P/E approaches the 2-year low P/E. This leads to rejecting the Hypothesis 4 but results are in line with the anchoring effect found on the 52-week low stock price. From Panel B, it is also seen that without additional control variables, the *Approach 3-year low P/E* and *Approach 5-year low P/E* dummies show some statistical significance at the 5% level and at the 10% level, respectively. However, since these dummies yield insignificant results when taking into account the additional controls, I conclude that the 2-year ratios are the most important ratios. Further regressions including valuation multiples with other time periods than the 2-year time periods are out of the scope of this thesis and left for further studies to examine[12].

To confirm the importance of the 2-year high and low ratios, Figure 4 and Figure 5 illustrate the log odds ratios and statistical significance of *Approach 2-year high P/E* and *Approach 2-year low P/E* dummies with various thresholds for the nearness of forward-looking P/E ratio to the 2-year high and low P/E ratios ranging from 1% up to 30% below and above the 2-year high and low P/E ratio, respectively. To have high comparability with Figure 2 and Figure 3, only the same control variables are included in regressions as in Figures 2 and 3. Thus, the anchoring effects can be more easily compared between all Figures 2-5. Results in Figures 4 and 5 give further support for the results in this section that analysts partly anchor their recommendation revisions to the 2-year high and low P/E ratios. However, the impact is two times higher with Approach dummies of 52-week high and low stock prices. In Figure 4, log odds ratios are of similar size to results in Table 14 when the *Approach* dummy is defined as 4-8% below the 2-year high P/E and *Approach* dummy stays statistically significant until the threshold of 28%. In Figure 5, somewhat similar log odds ratios to results in Table 14 are obtained when the

[12] To cite a few additional interesting periods to examine: all-time high and low P/E ratios and Schillers cyclically adjusted high and low P/E ratios.

Approach dummy is defined as 3-6% above the 2-year low P/E and *Approach* dummy stays statistically significant until the threshold of 10%.

Table 15 shows the correlation matrix of different *Approach* dummies. Panel A shows correlations with approaching high dummies with 5% threshold below the high price or ratio. Panel B shows correlations with approaching low dummies with 5% threshold above the low price or ratio. Panel C includes the correlations between the select approaching high and low dummies that are used in the main tests of this thesis. These include the 52-week high and low stock price dummies, the 2-year high and low P/E dummies and 5% below the target price dummy. In the end of this section, regressions are run including all of these dummies and control variables.

Firstly, Table 15 shows that there is a high correlation between the dummies of approaching the 52-week high stock price and the 2-year high stock price (Correlation of 0.784 in Panel A). The correlation is also high between the dummies of approaching the 52-week low stock price and the 2-year low stock price (Correlation of 0.565 in Panel B). As a result, it is highly likely that similar, statistically significant results are obtained by either using 52-week high and low stock price or the 2-year high and low stock price dummies[13]. Due to a very high correlation, I only use 52-week high and low stock price dummies in the regressions.

Secondly, Table 15 shows the correlations between the valuation multiples. Panel A shows the correlations between the 2-year high P/E, PEG, EV/EBITDA, EV/EBIT and EV/Sales. Panel B shows the correlations between the 2-year low P/E, PEG, EV/EBITDA, EV/EBIT and EV/Sales. The correlations between the Enterprise value (EV) multiples are high, ranging from 0.368 to 0.665. Particularly high correlations are between EV/EBITDA and EV/EBIT (0.665 between high dummies and 0.547 between low dummies) and EV/EBITDA and EV/Sales (0.548 between high dummies and 0.479 between low dummies). In addition, very high correlations are found between the P/E and PEG ratios (0.506 between high dummies and 0.527 between low dummies). Furthermore, it is seen that P/E ratio has correlation to EV multiples as well, with correlation ranging from 0.283 to 0.362. Thus, it is likely that regression results by using EV multiples or PEG ratio would be consistent to regressions with P/E ratio. However, as discussed in Introduction and Literature review, the analysts use P/E ratios to justify their

[13] Robustness check in Table 23 confirms the assumption and reports the coefficients of 2-year high and low stock price dummies with and without 52-week high and low stock price dummies.

recommendations and thus it is likely that regression results are weaker with EV multiples. Section 5.5 includes regressions with EV multiples and PEG ratios.

Thirdly, Panel C in Table 15 shows that between the select approaching high and low dummies, there is somewhat high correlation between approaching 52-week high stock price and approaching 2-year high P/E (Correlation of 0.349) and between approaching 52-week low stock price and approaching 2-year low P/E (Correlation of 0.369). Thus, the high (low) points of 52-week high and 2-year high (low) somewhat coincide with each other. As a result, I also check robustness of the regression results by adding interaction terms between these dummies. On top of that, Panel C shows that between other approach dummies, the correlations are rather close to zero, being 0.144 at highest.

Last part of this section shows the results from the conditional logit regressions with all the select approaching high and low dummies (the same as in Panel C of Table 15) that are seen to have effect on downgrades. Table 16 shows the results without the interaction terms and Table 17 with interaction terms. All regressions include the usual control variables used in earlier sections as well as year and industry fixed effects. The Wald-chi squared statistics are statistically significant at the 1% level in all model specifications, confirming the overall significance of the results. Interaction term of *2-year high # 52-week high* shows the effect when forward-looking P/E is approaching the 2-year high P/E ratio and stock price is approaching the 52-week high at the same time. Similarly, interaction term of *2-year low # 52-week low* shows the effect when these dummies are approaching the corresponding low values at the same time.

Table 16 shows the conditional logistic regression results without interaction terms. Results indicate that the 52-week high and low phenomena are important anchors for analysts as both dummies are statistically significant at the 1% level in all five models. It is also seen that *Forecast revisions* and *Return* $_{t-21,\ t-6}$ seem to be most important factors to affect downgrade decisions which is in line with all earlier results. There seems to be also some statistical significance found from *Approach 2-year high P/E*, *Targer price high 5%* and *Approach 2-year low P/E* dummies but all of them are only statistically significant at the 10% level in Model 5. This is also in line with earlier regression results.

Table 17 shows the effect of 52-week high and low stock price and 2-year high and low P/E ratio on recommendation downgrade with two interaction terms. It seems that interaction terms are statistically significant at the 1-5% level in all five models. In addition, the direction of the coefficient of the interaction term *2-year low # 52-week low* is negative (-0.653) in Model 5, indicating that when stock price is approaching the 52-week low and P/E ratio is approaching the 2-year low, the analyst is more likely to upgrade the stock. This is new insight, which is actually in line with Hypothesis 2 and 4. The situation is also illustrated in Figure 1 where an analyst upgrades his recommendation in a similar situation. One interpretation of this result is that analysts see the stock price and P/E ratio to have reached a support level so that the stock price cannot go much lower anymore and hence they overreact in the situation and revise their recommendations upwards. Thus, odds of being downgraded are 48.0% lower for companies with stock prices approaching the 52-week low stock prices and at the same time with forward-looking P/E ratios approaching the 2-year low P/E ratios than that of other companies[14].

Furthermore, Table 17 shows that *Approach52* and *Approach52low* are statistically significant at 1% level in all five models, supporting the anchoring hypotheses. The effect of anchoring seems to be slightly higher when the stock price is approaching the 52-week high and forward-looking P/E is approaching the 2-year high (Coefficient of 0.332) compared to only approaching the 52-week high stock price (Coefficient of 0.318). However, it seems that *2-year high P/E* dummy does not play significant role alone as it yields insignificant results and the coefficient is slightly negative and close to zero. Instead, the *2-year low P/E* dummy remains statistically significant at the 1% level in Model 5. In addition, *Target price high 5%* remains statistically significant at the 10% level in Model 5. Also, *Forecast revisions* and $Return_{t-21,\, t-6}$ are still the most important factors to affect downgrade decision, consistent with earlier findings and prior literature.

[14] Regression odds ratio of 0.520 in Model 5 in Table 17.

Table 14. The effect of high and low P/E ratios on recommendation downgrades

This table shows the predictability of approaching the high and low forward-looking P/E ratios on recommendation downgrades. Conditional logit regression is: $Downgrade_{j,t} = \beta_0 + \beta_1 Approach\ P/E\ frwd_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. Dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach P/E frwd* equals 1 if forward-looking P/E at day t-1 is within 5% below (above) the high (low) P/E ratio in Panel A (in Panel B). The P/E ratio that the approach dummy is approaching is indicated in the column headlines, from 1-year high up to 10-year high P/E ratios in Panel A and from 1-year low up to 10-year low P/E ratios in Panel B. Regressions are tested with additional control variables of *Approach52*, *Target*, *Apporach52low* which are seen to affect the downgrades in earlier regressions. *Approach52* (*Approach52low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low). *Target* is a dummy that equals 1 if stock price at day t-1 is within 5% below the target price issued by the same analyst who revises the recommendation. Vector X includes a set of control variables that are not reported and definitions of control variables are found in Table 5. All regressions control for year and SIC 10 industry fixed effects. Additional control variables are added when specified. Coefficients are reported as log odds ratios and *z*-statistics are based on two-way clustered standard errors by firm and year. Sig. denotes for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

Panel A: The effect of high P/E on downgrades

	Approach 1-year high P/E						Approach 2-year high P/E						Approach 3-year high P/E						Approach 5-year high P/E						Approach 10-year high P/E					
Downgrade	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach P/E frwd	0.202	***	3.61	0.039		0.65	0.282	***	3.99	0.139	*	1.90	0.178	*	1.90	0.035		0.37	0.114		0.70	-0.004		-0.03	0.092		0.32	-0.019		-0.07
Additional controls	No			Yes			No			Yes			No			Yes			No			Yes			No			Yes		
Approach52				0.357	***	7.16				0.346	***	7.36				0.366	***	7.90				0.370	***	8.08				0.370	***	8.09
Target				0.146	*	1.84				0.144	*	1.80				0.148	*	1.85				0.148	*	1.87				0.148	*	1.87
Approach52low				0.386	***	5.50				0.387	***	5.51				0.387	***	5.50				0.386	***	5.49				0.386	***	5.49
Controls	Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes		
Observations	17,508			17,508			17,508			17,508			17,508			17,508			17,508			17,508			17,508			17,508		
Wald chi^2	248.69			347.67			254.07			352.20			238.44			347.21			235.36			347.30			234.04			347.11		
Pseudo R^2	0.015			0.019			0.015			0.019			0.015			0.019			0.015			0.019			0.015			0.019		

Panel B: The effect of low P/E ratio on downgrades

	Approach 1-year low P/E						Approach 2-year low P/E						Approach 3-year low P/E						Approach 5-year low P/E						Approach 10-year low P/E					
Downgrade	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach P/E frwd	0.078		1.25	-0.007		-0.10	0.275	***	2.99	0.179	*	1.80	0.283	**	2.51	0.168		1.41	0.354	*	1.93	0.241		1.28	0.196		0.50	0.062		0.15
Additional controls	No			Yes			No			Yes			No			Yes			No			Yes			No			Yes		
Approach52				0.369	***	8.02				0.372	***	8.09				0.371	***	8.07				0.371	***	8.06				0.370	***	8.05
Target				0.128	*	1.87				0.150	*	1.90				0.149	*	1.89				0.149	*	1.88				0.148	*	1.87
Approach52low				0.388	***	5.05				0.338	***	4.40				0.356	***	4.81				0.365	***	5.05				0.384	***	5.43
Controls	Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes			Yes		
Observations	17,508			17,508			17,508			17,508			17,508			17,508			17,508			17,508			17,508			17,508		
Wald chi^2	233.51			347.25			241.45			349.87			238.61			347.89			238.44			348.05			234.49			347.15		
Pseudo R^2	0.015			0.019			0.015			0.019			0.015			0.019			0.015			0.019			0.015			0.019		

Figure 4. The log odds ratio of being downgraded with nearness to the 2-year high P/E

Figure 4 shows the log odds ratio of being downgraded with nearness to the 2-year high P/E ratio. Approaching 2-year high dummy equals 1 if the P/E at trading day t-1 is within x% below the 2-year high P/E, i.e. (1-x) × 2-year high P/E < P/E at day t-1 < 2-year high P/E. Results are based on conditional logit regression with all control variables defined in Table 5. The logit regression is: $Downgrade_{j,t} = \beta_0 + \beta_1 Approach\ 2\ year\ high_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. Plotted coefficients are reported as log odds ratios. See Panel A in Table 14 for more information on regressions with Approaching 2 year high dummy that has a threshold of 5% below the 2-year high P/E.

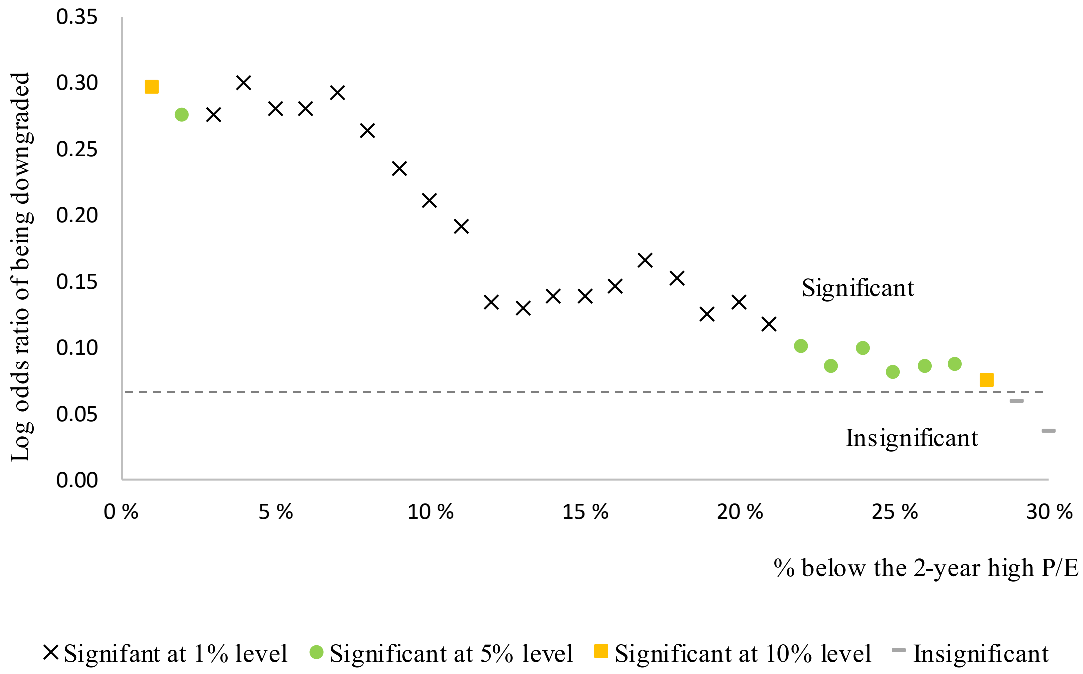


Figure 5. The log odds ratio of being downgraded with nearness to the 2-year low P/E

Figure 5 shows the log odds ratio of being downgraded with nearness to the 2-year low P/E ratio. Approaching 2-year low dummy equals 1 if the P/E at trading day t-1 is within x% above the 2-year low P/E ratio, i.e. 2-year low P/E < P/E at day t-1 < (1+x) × 2-year low P/E. Results are based on conditional logit regression with all control variables defined in Table 5. The logit regression is: $Downgrade_{j,t} = \beta_0 + \beta_1 Approach\ 2\ year\ low_{j,t-1} + \delta' X_j + Industry\ FE + Year\ FE + \varepsilon_{j,t}$, where subscript j and t denote the recommendation revision j issued on day t. Plotted coefficients are reported as log odds ratios. See Panel B in Table 14 for more information on regressions with Approaching 2-year low P/E dummy that has a threshold of 5% above the 2-year low P/E.

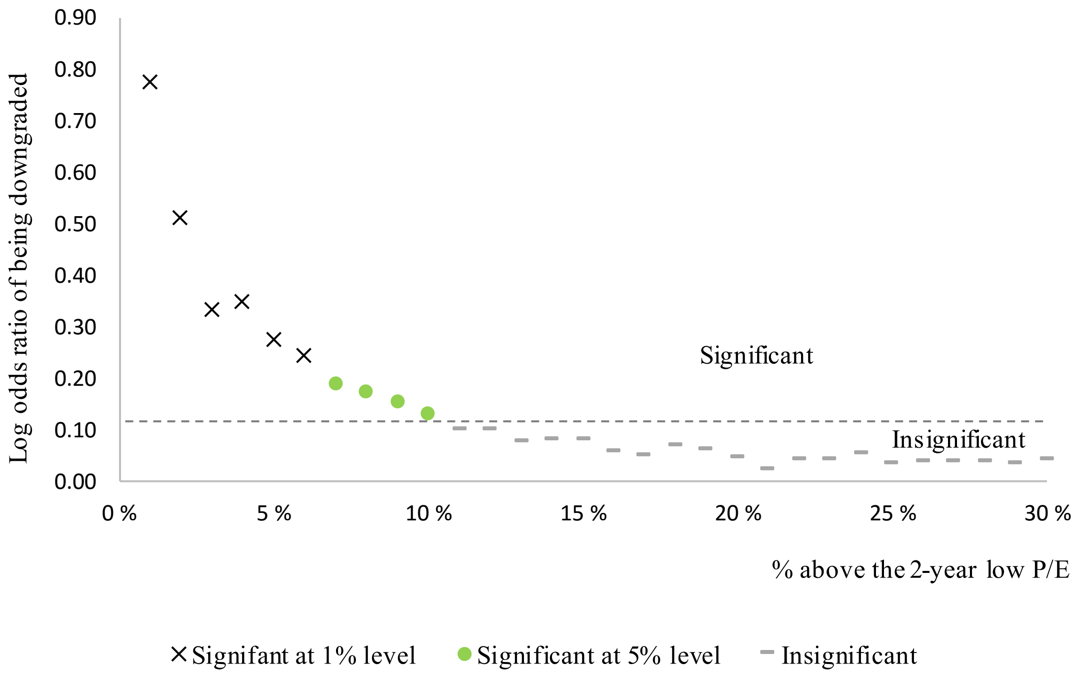


Table 15. Correlation matrix of approach dummies

This table reports the correlations between various approach dummies. Panel A shows the correlations between approaching high dummies, Panel B between approaching low dummies and Panel C between the select approaching high and low dummies used in the main tests and regressions in Table 16 and Table 17. Approaching high dummies are 1 if the value is within 5% below the high value/ratio of the defined time period and 0 otherwise. Approaching low dummies are 1 if the value is within 5% above the low value/ratio of the defined time period and 0 otherwise.

Panel A: Correlations with approaching high dummies

Approach dummies	52 week (1)	2 year (2)	Target (3)	P/E (4)	PEG (5)	EV/EBITDA (6)	EV/EBIT (7)	EV/Sales (8)
52 week high stock price (1)	1.000							
2 year high stock price (2)	0.784	1.000						
Below target price 5% (3)	0.144	0.127	1.000					
2 year high P/E (4)	0.349	0.415	0.081	1.000				
2 year high PEG (5)	0.257	0.277	0.060	0.506	1.000			
2 year high EV/EBITDA (6)	0.222	0.265	0.115	0.362	0.170	1.000		
2 year high EV/EBIT (7)	0.177	0.207	0.109	0.351	0.170	0.665	1.000	
2 year high EV/Sales (8)	0.291	0.359	0.133	0.315	0.174	0.548	0.442	1.000

Panel B: Correlations with approaching low dummies

Approach dummies	52 week (1)	2 year (2)	Target (3)	P/E (4)	PEG (5)	EV/EBITDA (6)	EV/EBIT (7)	EV/Sales (8)
52 week low stock price (1)	1.000							
2 year low stock price (2)	0.565	1.000						
Above target price 5% (3)	-0.049	-0.028	1.000					
2 year low P/E (4)	0.369	0.287	-0.045	1.000				
2 year low PEG (5)	0.254	0.189	-0.038	0.527	1.000			
2 year low EV/EBITDA (6)	0.197	0.174	-0.022	0.322	0.186	1.000		
2 year low EV/EBIT (7)	0.153	0.133	-0.022	0.283	0.184	0.547	1.000	
2 year low EV/Sales (8)	0.271	0.263	-0.031	0.313	0.187	0.479	0.368	1.000

Panel C: Correlations with select approaching high and low dummies

Approach dummies	52 high (1)	Target (2)	P/E high (3)	52 low (4)	P/E low (5)
52 week high stock price (1)	1.000				
Below target price 5% (2)	0.144	1.000			
2 year high P/E (3)	0.349	0.081	1.000		
52 week low stock price (4)	-0.101	-0.049	-0.045	1.000	
2 year low P/E (5)	-0.073	-0.045	-0.044	0.369	1.000

Table 16. The effect of 52-week high and low stock price and 2-year high and low P/E ratio on recommendation downgrade (Without interaction terms)

This table shows results of conditional logit regression where dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach 52 week high* (*Approach 52 week low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low). *Approach 2 year high P/E* (*Approach 2 year low P/E*) is a dummy that equals 1 if P/E at day t-1 is within 5% below (above) the 2 year high (low). *Target price high 5%* is a dummy that equals 1 if stock price at day t-1 is within 5% below the target price issued by the same analyst who revises the recommendation. *Return* variables denote for cumulative return between days t or months m, where $Return_{t-5,\, t-1}$ is from day t-5 to t-1, $Return_{t-21,\, t-6}$ is from day t-21 to t-6, $Return_{m-6,\, m-2}$ is from month -6 to month -2, and $Return_{m-12,\, m-7}$ is from month -12 to month -7. *Forecast revisions* is rolling sum of previous six months' EPS revisions to price ratio. *SUE* is the standardized unexpected earnings. *Size* is the natural logarithm of market value at day t-22. *B/M* is book value of equity divided by market value of equity. *P/E* is price-to-earnings ratio based on actual earnings in the last available fiscal year. *Turnover* is average daily turnover in the previous three months divided by shares outstanding. *Accruals* are total accruals divided by average total assets on a quarterly basis. *Capex* is rolling sum of capital expenditure in the previous four quarters divided by average total assets. *Sales growth* is the rolling sum of sales in the previous four quarters divided by rolling sum of sales in the second preceding set of four quarters. *LTG* is median consensus long-term growth forecast. *Idiosyncratic volatility* is the standard deviation of the residuals of FF3-factor model. *Institutional ownership* is the ownership of institutes in percentages. *Analyst coverage* is number of analysts providing one-year earnings forecasts in prior three months. *Analyst dispersion* is the standard deviation across earnings forecasts in the prior three months. *Analyst experience* is the natural logarithm of recommendation revision year minus number of years plus one (or 0 if negative) since the analyst gave its first EPS estimate for the firm in question. Full definitions of control variables are found in Table 5. All regressions control for year and SIC 10 industry fixed effects. Coefficients are reported as log odds ratios and *z*-statistics are based on two-way clustered standard errors by firm and year. OR denotes for Odds ratio and Sig. for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

Cond. logit model	(1)				(2)				(3)				(4)				(5)			
Downgrade	Coef.	OR	Sig.	*z*-stat	Coef.	OR	Sig.	*z*-stat	Coef.	OR	Sig.	*z*-stat	Coef.	OR	Sig.	*z*-stat	Coef.	OR	Sig.	*z*-stat
Approach 52 week high	0.300	1.350	***	8.49	0.292	1.339	***	7.86	0.305	1.356	***	8.02	0.331	1.392	***	6.72	0.349	1.417	***	7.41
Approach 2 year high P/E	0.135	1.145	**	2.51	0.126	1.134	**	2.31	0.085	1.089		1.53	0.153	1.166	**	2.18	0.138	1.148	*	1.89
Target price high 5%	0.118	1.125	**	2.57	0.100	1.105	**	2.03	0.080	1.084		1.61	0.133	1.143	*	1.86	0.146	1.158	*	1.84
Approach 52 week low	0.312	1.366	***	5.65	0.351	1.420	***	6.12	0.322	1.380	***	5.51	0.350	1.419	***	4.67	0.339	1.404	***	4.43
Approach 2 year low P/E	-0.035	0.965		-0.55	0.014	1.014		0.21	0.077	1.080		1.17	0.167	1.181	*	1.73	0.179	1.196	*	1.79
$Return_{t-5,\, t-1}$					-0.076	0.927		-0.33	0.144	1.155		0.61	-0.018	0.982		-0.05	0.057	1.059		0.11
$Return_{t-21,\, t-6}$					1.782	5.942	***	11.74	1.948	7.015	***	12.16	2.125	8.370	***	6.58	2.194	8.970	***	4.28
$Return_{m-6,\, m-2}$					-0.379	0.685	***	-6.98	-0.225	0.798	***	-3.77	-0.118	0.889		-1.09	-0.097	0.907		-0.93
$Return_{m-12,\, m-7}$					-0.146	0.864	***	-2.85	-0.080	0.923		-1.47	-0.015	0.985		-0.22	-0.048	0.954		-0.45
Forecast revisions									-6.399	0.002	***	-7.06	-5.189	0.006	***	-4.35	-4.764	0.009	***	-4.01
SUE									0.014	1.014		1.31	-0.002	0.998		-0.17	-0.007	0.993		-0.43
Size													-0.009	0.991		-0.05	0.037	1.038		0.10
B/M													0.331	1.393		0.66	0.331	1.392		0.56
P/E													-0.001	0.999	**	-2.05	-0.001	0.999		-1.31
Turnover													0.008	1.008	***	2.68	0.003	1.003		1.08
Accruals													0.325	1.383		0.66	0.243	1.275		0.60
Capex													-0.037	0.964		-0.07	0.070	1.072		0.06
Sales growth													0.319	1.375		0.61	0.276	1.318		0.59
LTG													0.003	1.003		0.31	0.001	1.001		0.06
Idiosyncratic volatility																	9.615	14986		0.59
Institutional ownership																	0.178	1.195		0.43
Analyst coverage																	-0.619	0.538		-0.17
Analyst dispersion																	-0.161	0.851		-0.45
Analyst experience																	-0.004	0.996		-0.88
Analyst herding																	0.278	1.320	***	3.47
Year fixed effects	Yes				Yes				Yes				Yes				Yes			
Industry fixed effects	Yes				Yes				Yes				Yes				Yes			
Observations	35,258				30,001				28,562				17,684				17,508			
Wald chi^2	122.74				341.28				361.68				318.10				354.84			
Pseudo R^2	0.003				0.011				0.013				0.018				0.020			

Table 17. The effect of 52-week high and low stock price and 2-year high and low P/E ratio on recommendation downgrade (With interaction terms)

This table shows results of conditional logit regression where dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach 52 week high* (*Approach 52 week low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low). *Approach 2 year high P/E* (*Approach 2 year low P/E*) is a dummy that equals 1 if P/E at day t-1 is within 5% below (above) the 2 year high (low). Interaction term is 1 if *Approach 52 week high* (*Approach 52 week low)* and *Approach 2 year high* (*Approach 2 year low*) are both 1. *Target price high 5%* is a dummy that equals 1 if stock price at day t-1 is within 5% below the target price issued by the same analyst who revises the recommendation. *Return* variables denote for cumulative return between days t or months m, where $Return_{t-5,\ t-1}$ is from day t-5 to t-1, $Return_{t-21,\ t-6}$ is from day t-21 to t-6, $Return_{m-6,\ m-2}$ is from month -6 to month -2, and $Return_{m-12,\ m-7}$ is from month -12 to month -7. *Forecast revisions* is rolling sum of previous six months' EPS revisions to price ratio. *SUE* is the standardized unexpected earnings. *Size* is the natural logarithm of market value at day t-22. *B/M* is book value of equity divided by market value of equity. *P/E* is price-to-earnings ratio based on actual earnings in the last available fiscal year. *Turnover* is average daily turnover in the previous three months divided by shares outstanding. *Accruals* are total accruals divided by average total assets on a quarterly basis. *Capex* is rolling sum of capital expenditure in the previous four quarters divided by average total assets. *Sales growth* is the rolling sum of sales in the previous four quarters divided by rolling sum of sales in the second preceding set of four quarters. *LTG* is median consensus long-term growth forecast. *Idiosyncratic volatility* is the standard deviation of the residuals of FF3-factor model. *Institutional ownership* is the ownership of institutes in percentages. *Analyst coverage* is number of analysts providing one-year earnings forecasts in prior three months. *Analyst dispersion* is the standard deviation across earnings forecasts in the prior three months. *Analyst experience* is the natural logarithm of recommendation revision year minus number of years plus one (or 0 if negative) since the analyst gave its first EPS estimate for the firm in question. Full definitions of control variables are found in Table 5. All regressions control for year and SIC 10 industry fixed effects. Coefficients are reported as log odds ratios and *z*-statistics are based on two-way clustered standard errors by firm and year. OR denotes for Odds ratio and Sig. for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

Cond. logit model	(1)				(2)				(3)				(4)				(5)			
Downgrade	Coef.	OR	Sig.	*z*-stat	Coef.	OR	Sig.	*z*-stat	Coef.	OR	Sig.	*z*-stat	Coef.	OR	Sig.	*z*-stat	Coef.	OR	Sig.	*z*-stat
Approach 52 week high	0.268	1.308	***	7.23	0.254	1.289	***	6.47	0.266	1.304	***	6.62	0.301	1.351	***	5.74	0.318	1.374	***	6.40
Approach 2 year high P/E	-0.106	0.899		-1.17	-0.141	0.868		-1.54	-0.188	0.828	**	-2.02	-0.042	0.959		-0.37	-0.063	0.939		-0.55
2 year high # 52-week high																				
1 1	0.384	1.469	***	3.34	0.422	1.525	***	3.64	0.432	1.540	***	3.67	0.323	1.381	**	2.18	0.332	1.394	**	2.23
Target price high 5%	0.123	1.131	***	2.68	0.105	1.110	**	2.12	0.085	1.089	*	1.71	0.136	1.145	*	1.89	0.149	1.161	*	1.87
Approach 52 week low	0.439	1.550	***	6.87	0.489	1.631	***	7.36	0.467	1.595	***	6.87	0.481	1.617	***	5.73	0.476	1.610	***	5.56
Approach 2 year low P/E	0.202	1.224	**	2.44	0.265	1.304	***	3.19	0.335	1.398	***	4.01	0.403	1.496	***	3.29	0.427	1.532	***	3.58
2 year low # 52-week low																				
1 1	-0.612	0.542	***	-4.57	-0.646	0.524	***	-4.80	-0.665	0.514	***	-4.94	-0.621	0.538	***	-3.47	-0.653	0.520	***	-3.76
$Return_{t-5,\ t-1}$					-0.011	0.989		-0.05	0.212	1.236		0.89	0.035	1.035		0.09	0.112	1.118		0.22
$Return_{t-21,\ t-6}$					1.809	6.102	***	11.88	1.978	7.227	***	12.30	2.147	8.562	***	6.65	2.218	9.188	***	4.33
$Return_{m-6,\ m-2}$					-0.370	0.691	***	-6.82	-0.215	0.807	***	-3.60	-0.112	0.894		-1.04	-0.091	0.913		-0.87
$Return_{m-12,\ m-7}$					-0.149	0.861	***	-2.91	-0.083	0.921		-1.52	-0.019	0.981		-0.27	-0.051	0.951		-0.49
Forecast revisions									-6.424	0.002	***	-7.08	-5.204	0.005	***	-4.35	-4.785	0.008	***	-4.02
SUE									0.014	1.014		1.27	-0.003	0.997		-0.20	-0.007	0.993		-0.45
Size													-0.009	0.991		-0.05	0.037	1.037		0.10
B/M													0.324	1.383		0.64	0.324	1.382		0.54
P/E													-0.001	0.999	**	-2.03	-0.001	0.999		-1.30
Turnover													0.008	1.008	***	2.64	0.003	1.003		1.03
Accruals													0.336	1.400		0.68	0.256	1.292		0.64
Capex													-0.022	0.978		-0.04	0.090	1.094		0.08
Sales growth													0.312	1.366		0.60	0.270	1.310		0.58
LTG													0.003	1.003		0.32	0.001	1.001		0.07
Idiosyncratic volatility																	9.635	15285		0.59
Institutional ownership																	0.182	1.200		0.44
Analyst coverage																	-0.614	0.541		-0.17
Analyst dispersion																	-0.169	0.844		-0.48
Analyst experience																	-0.004	0.996		-0.89
Analyst herding																	0.278	1.320	***	3.47
Year fixed effects	Yes				Yes				Yes				Yes				Yes			
Industry fixed effects	Yes				Yes				Yes				Yes				Yes			
Observations	35,258				30,001				28,562				17,684				17,508			
Wald chi^2	148.84				369.91				392.00				330.14				372.18			
Pseudo R^2	0.004				0.012				0.015				0.018				0.020			

5.5 Robustness checks for the anchoring effects of the P/E ratio and testing the consistency of results with other valuation multiples

This section shows the results from additional regressions, supporting the evidence found from earlier sections. First, anchoring of P/E ratio on recommendation downgrades is tested with alternative definitions of P/E ratios using mean forward-looking ratios and actual P/E ratios instead of median forward-looking ratios[15]. Second, it is tested whether the anchoring effect is found by using different forward-looking valuation multiples. Third, the main regression results from Table 16 are tested by using OLS and probit models. Fourth, robustness of results is tested by running subsample regressions on each weekday. Finally, the consistency of results is tested with actual values instead of forward-looking values.

Table 18 shows the conditional logit regression results with alternative definitions of P/E ratios. Compared to results in Table 14, results are strongest with median forward-looking P/E ratios while mean forward-looking ratios come second and the weakest results are obtained with actual P/E ratios. The result is in line with Liu et al. (2001) who show that forward-looking earnings explain future returns more than historical ones. Approach dummies based on actual P/E ratios and mean forward-looking ratios are statistically significant without additional control variables. However, after taking into account additional control variables, both *Approach 2-year high* and *Approach 2-year low P/E* dummies lose statistical significance. When it comes to approach dummies based on mean forward-looking values, the results are rather robust with median forward-looking values. With additional control variables included, coefficient is 0.139 for median 2-year high dummy (See Table 14) whereas for mean 2-year high dummy it is 0.055. With mean values, the dummy loses statistical significance. In the case of 2-year low dummies, the mean dummy's coefficient is 0.221 whereas the median dummy's coefficient is 0.179. Both cases are statistically significant at the 10% level.

Table 19 shows regression results with different forward-looking valuation multiples with and without additional control variables. From valuation multiples, the anchoring effect seems to be strongest with the forward-looking P/E dummies. Without additional control variables, anchoring effects are also seen from forward-looking EV/EBITDA dummies and high EV/Sales dummy as well as low PEG ratio dummy. When additional control variables are included, only approaching 2-year high and low forward-looking P/E dummies and approaching 2-year low PEG dummy seem to show statistical significance. The similar results are obtained most likely

[15] The ratios are based on consensus EPS estimates, and using the analysts own EPS estimates who make the recommendation revision is left for further studies.

because there is a high correlation of 0.527 between approach dummies of low P/E and PEG ratio as shown in Panel C of Table 15. Nevertheless, based on these results forward-looking EV multiples are not the driving the anchoring effects.

Table 20 shows similar analysis to Table 19 but with historical-looking approach dummies. It includes 2-year high and low stock price dummies and actual P/E and actual EV based multiples. Results are robust with forward-looking values when additional control variables are included. It also shows that 2-year high and low stock price dummies are statistically significant at the 1% level without additional control variables and at the 1-5% level with additional control variables. It confirms the assumption made in Section 5.4 that results are similar to 52-week high and low dummies because the correlation between 52-week high (and low) and 2-year high (and low) stock prices is 0.784 (and 0.565).

Table 21 and Table 22 show regression results based on OLS and probit regressions, similarly to the main test in Table 16. Both regressions support the importance of 52-week high and 52-week low dummies, showing statistical significance at the 1% level in all model specifications. *Target price high 5%*, *Approaching 2-year high P/E* and *Approaching 2-year low P/E* dummies show statistical significance at the 5-10% level in probit regression (Model 5) but lose statistical significance in OLS regression (Model 5) except for the *Approaching 2-year low P/E* dummy which stays significant at the 10% level. It is also seen that *Forecast revisions* and *Return* $_{t-21,\ t-6}$ are most important factors to affect downgrade decisions which is in line with all earlier results.

Table 23 shows the robustness of results with subsamples based on weekdays. Regressions are run separately for each weekday to see if the results differ e.g. in the beginning of the week. It reveals whether variables that are based on shorter time periods show any differences between weekdays, such as Return variables. Recent price momentum is partly captured by two variables that are based on a relatively short time period: *Return* $_{t-5,\ t-1}$ are *Return* $_{t-21,\ t-6}$. The subsample results show that *Forecast revisions* and *Return* $_{t-21,\ t-6}$ are not statistically significant anymore in all weekdays. *Return* $_{t-21,\ t-6}$ is statistically significant at the 10% level in three days and insignificant in other weekdays. *Forecast revisions* is statistically significant at the 1% level on Monday and at the 5% level on Wednesday and insignicant on Tuesday, Thursday and Friday. The magnitude and direction of coefficients are robust with results in earlier sections for both *Return* and *Forecast revisions* variables.

Moreover, it seems that 52-week high and low dummies are the most important factors with this subsample. *Approach 52 week high* is statistically significant at the 1% level in Monday, Tuesday, Wednesday and Friday and at the 5% level in Thursday. The magnitude and direction of the coefficients is also in line with the main results, ranging from 0.287 on Friday to 0.426 on Tuesday. *Approach 52 week low* is statistically significant at the 5% level on Wednesday and Friday and at the 10% level on Monday and Tuesday and insignificant on Thursday. The magnitude and direction of the coefficients are robust with the main tests in the earlier sections. Results support the significance of anchoring effect of the 52-week high and low phenomena and indicate that historical stock prices are more important reference points in analyst decision making than reference points based on valuation ratios.

Table 18. Alternative definitions of P/E ratios

This table shows the conditional logit regression results with alternative definitions of P/E ratios. Dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach 2-year high* (*low*) dummy equals 1 if the *Approach* dummy is within 5% below (above) the P/E mean forward ratio or the P/E actual ratio. Regressions are tested with and without additional control variables of *Approach52*, *Target*, *Apporach52low* which are seen to affect the downgrades in earlier regressions. *Approach52* (*Approach52low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low). *Target* is a dummy that equals 1 if stock price at day t-1 is within 5% below the target price issued by the same analyst who revises the recommendation. Coefficients of additional control variables and control variables are not reported. Definitions of control variables are found in Table 5. All regressions control for year and SIC 10 industry fixed effects. Coefficients are reported as log odds ratios and z-statistics are based on two-way clustered standard errors by firm and year. Additional control variables are added when specified.

Cond. logit model	P/E mean forward			P/E mean forward			P/E actual			P/E actual		
Downgrade	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach 2 year high P/E	0.196	**	2.29	0.055		0.64	0.229	***	3.06	0.029		0.36
Approach 2 year low P/E	0.327	***	2.93	0.221	*	1.89	0.280	**	2.18	0.091		0.69
Additional controls	No			Yes			No			Yes		
Controls	Yes			Yes			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes		
Observations	17,508			17,508			17,508			17,508		
Wald chi^2	247.06			348.74			252.92			347.28		
Pseudo R^2	0.015			0.019			0.015			0.019		

Table 19. Different forward-looking valuation multiples

This table shows the conditional logit regression results with different forward-looking valuation multiples. Dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach 2-year high* (*low*) dummy equals 1 if the *Approach* dummy is within 5% below (above) the ratio defined in the headline of the Columns 2-6. Regressions are tested with and without additional control variables of *Approach52*, *Target*, *Apporach52low* which are seen to affect the downgrades in earlier regressions. *Approach52* (*Approach52low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low). *Target* is a dummy that equals 1 if stock price at day t-1 is within 5% below the target price issued by the same analyst who revises the recommendation. Coefficients of additional control variables and control variables are not reported. Definitions of control variables are found in Table 5. All regressions control for year and SIC 10 industry fixed effects. Coefficients are reported as log odds ratios and *z*-statistics are based on two-way clustered standard errors by firm and year. Additional control variables are added when specified.

Cond. logit model	Forward P/E ratio			Forward PEG-ratio			Forward EV/EBITDA			Forward EV/EBIT			Forward EV/Sales		
Downgrade	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat
Approach 2 year high (variable)	0.285	***	4.02	0.120		1.49	0.240	**	2.59	0.094		0.86	0.231	***	2.75
Approach 2 year low (variable)	0.279	***	3.03	0.315	***	2.77	0.257	**	2.24	0.236		1.55	0.147		1.45
Additional controls	No			No			No			No			No		
Controls	Yes			Yes			Yes			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes		
Observations	17,508			16,335			7,418			5,526			11,129		
Wald chi^2	261.90			218.77			246.58			172.16			246.88		
Pseudo R^2	0.016			0.014			0.031			0.029			0.024		

Cond. logit model	Forward P/E ratio			Forward PEG-ratio			Forward EV/EBITDA			Forward EV/EBIT			Forward EV/Sales		
Downgrade	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat
Approach 2 year high (variable)	0.138	*	1.89	0.012		0.15	0.111		1.13	-0.045		-0.38	0.073		0.80
Approach 2 year low (variable)	0.179	*	1.79	0.240	**	2.05	0.174		1.47	0.190		1.24	0.038		0.35
Additional controls	Yes			Yes			Yes			Yes			Yes		
Controls	Yes			Yes			Yes			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes		
Observations	17,508			16,335			7,418			5,526			11,129		
Wald chi^2	354.84			308.57			284.36			207.54			306.42		
Pseudo R^2	0.020			0.018			0.034			0.033			0.028		

Table 20. Alternative historical-looking approach dummies

This table shows the conditional logit regression results with different historical-looking valuation multiples. Dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach 2-year high* (*low*) dummy equals 1 if the *Approach* dummy is within 5% below (above) the ratio defined in the headline of the Columns 2-6. Regressions are tested with and without additional control variables of *Approach52*, *Target*, *Apporach52low* which are seen to affect the downgrades in earlier regressions. *Approach52* (*Approach52low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low). *Target* is a dummy that equals 1 if stock price at day t-1 is within 5% below the target price issued by the same analyst who revises the recommendation. Coefficients of additional control variables and control variables are not reported. Definitions of control variables are found in Table 5. All regressions control for year and SIC 10 industry fixed effects. Coefficients are reported as log odds ratios and z-statistics are based on two-way clustered standard errors by firm and year. Additional control variables are added when specified.

Cond. logit model	2-year stock price			Actual P/E ratio			Actual EV/EBITDA			Actual EV/EBIT			Actual EV/Sales		
Downgrade	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach high (variable)	0.399	***	7.11	0.259	***	4.19	0.218	**	2.18	0.241	**	2.40	0.232	***	2.93
Approach low (variable)	0.581	***	5.22	0.217	**	2.51	0.131		1.34	0.133		1.15	0.211	**	2.36
Additional controls	No			No			No			No			No		
Controls	Yes			Yes			Yes			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes		
Observations	17,508			17,508			7,418			5,526			11,129		
Wald chi^2	329.09			265.00			241.75			177.76			250.61		
Pseudo R^2	0.019			0.016			0.030			0.029			0.024		

Cond. logit model	2-year stock price			Actual P/E ratio			Actual EV/EBITDA			Actual EV/EBIT			Actual EV/Sales		
Downgrade	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat	Coef.	Sig.	z-stat
Approach high (variable)	0.187	**	2.09	0.057		0.83	0.057		0.52	0.076		0.72	0.055		0.65
Approach low (variable)	0.379	***	3.01	0.051		0.55	0.000		0.00	0.053		0.43	0.096		0.96
Additional controls	Yes			Yes			Yes			Yes			Yes		
Controls	Yes			Yes			Yes			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes		
Observations	17,508			17,508			7,418			5,526			11,129		
Wald chi^2	358.39			349.88			282.44			209.09			305.84		
Pseudo R^2	0.020			0.019			0.034			0.033			0.028		

Table 21. OLS regression

This table shows results of OLS regression where dependent variable is *Recommendation revision* which gets values between -4 to 4 where positive values indicate upgrades and negative values downgrades. *Approach 52 week high* (*Approach 52 week low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low) stock price. *Approach 2 year high P/E* (*Approach 2 year low P/E*) is a dummy that equals 1 if P/E at day t-1 is within 5% below (above) the 2 year high (low). *Target price high 5%* is a dummy that equals 1 if stock price at day t-1 is within 5% below the target price issued by the same analyst who revises the recommendation. *Return* variables denote for cumulative return between days t or months m, where $Return_{t-5,\ t-1}$ is from day t-5 to t-1, $Return_{t-21,\ t-6}$ is from day t-21 to t-6, $Return_{m-6,\ m-2}$ is from month -6 to month -2, and $Return_{m-12,\ m-7}$ is from month -12 to month -7. *Forecast revisions* is rolling sum of previous six months' EPS revisions to price ratio. *SUE* is the standardized unexpected earnings. *Size* is the natural logarithm of market value at day t-22. *B/M* is book value of equity divided by market value of equity. *P/E* is price-to-earnings ratio based on actual earnings in the last available fiscal year. *Turnover* is average daily turnover in the previous three months divided by shares outstanding. *Accruals* are total accruals divided by average total assets on a quarterly basis. *Capex* is rolling sum of capital expenditure in the previous four quarters divided by average total assets. *Sales growth* is the rolling sum of sales in the previous four quarters divided by rolling sum of sales in the second preceding set of four quarters. *LTG* is median consensus long-term growth forecast. *Idiosyncratic volatility* is the standard deviation of the residuals of FF3-factor model. *Institutional ownership* is the ownership of institutes in percentages. *Analyst coverage* is number of analysts providing one-year earnings forecasts in prior three months. *Analyst dispersion* is the standard deviation across earnings forecasts in the prior three months. *Analyst experience* is the natural logarithm of recommendation revision year minus number of years plus one (or 0 if negative) since the analyst gave its first EPS estimate for the firm in question. Full definitions of control variables are found in Table 5. All regressions control for firm and year fixed effects and *t*-statistics are based on two-way clustered standard errors by firm and year. Sig. denotes for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

OLS model	(1)			(2)			(3)			(4)			(5)		
Recommendation revision	Coef.	Sig.	*t*-stat	Coef.	Sig.	*t*-stat	Coef.	Sig.	*t*-stat	Coef.	Sig.	*t*-stat	Coef.	Sig.	*t*-stat
Approach 52 week high	-0.234	***	-9.23	-0.215	***	-8.15	-0.218	***	-8.11	-0.223	***	-6.39	-0.232	***	-6.59
Approach 2 year high P/E	-0.125	***	-3.22	-0.116	***	-2.98	-0.081	**	-2.05	-0.093	*	-1.81	-0.083		-1.60
Target price high 5%	-0.099	***	-2.92	-0.075	**	-2.09	-0.062	*	-1.70	-0.069		-1.50	-0.074		-1.58
Approach 52 week low	-0.238	***	-5.77	-0.266	***	-6.29	-0.240	***	-5.58	-0.247	***	-4.36	-0.236	***	-4.15
Approach 2 year low P/E	0.023		0.47	-0.014		-0.28	-0.057		-1.15	-0.099		-1.51	-0.110	*	-1.69
$Return_{t-5,\ t-1}$				-0.084		-0.49	-0.221		-1.25	-0.397	*	-1.76	-0.454	**	-2.02
$Return_{t-21,\ t-6}$				-1.355	***	-12.70	-1.432	***	-12.91	-1.804	***	-12.55	-1.829	***	-12.69
$Return_{m-6,\ m-2}$				0.244	***	6.18	0.127	***	2.97	-0.011		-0.20	-0.032		-0.56
$Return_{m-12,\ m-7}$				0.118	***	3.28	0.056		1.45	-0.015		-0.30	0.000		0.00
Forecast revisions							4.363	***	7.69	2.590	***	3.48	2.341	***	3.13
SUE							-0.010		-1.39	-0.002		-0.23	0.001		0.14
Size										-0.168	***	-5.50	-0.182	***	-5.00
B/M										-0.732	***	-8.93	-0.706	***	-8.48
P/E										0.002	***	3.05	0.002	***	2.78
Turnover										-0.007	***	-2.65	-0.003		-1.14
Accruals										-0.167		-0.64	-0.124		-0.48
Capex										-0.701	*	-1.78	-0.677	*	-1.69
Sales growth										-0.487	***	-6.12	-0.474	***	-5.85
LTG										0.002		0.84	0.004		1.23
Idiosyncratic volatility													-7.757	***	-3.83
Institutional ownership													-0.012		-0.12
Analyst coverage													-0.160		-0.50
Analyst dispersion													0.204	*	1.91
Analyst experience													0.005	**	2.08
Analyst herding													-0.216	***	-4.43
Intercept	-0.175		-1.53	-0.146		-1.20	-0.121		-0.99	4.407	***	6.11	7.740	***	5.84
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Firm fixed effects	Yes			Yes			Yes			Yes			Yes		
Observations	35,270			30,015			28,572			17,713			17,537		
F-test	13.68			17.55			17.60			13.19			12.72		
Adjusted R^2	-0.008			0.001			0.004			0.013			0.015		

Table 22. Probit regression

This table shows results of probit regression where dependent variable is *Downgrade* which is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach 52 week high* (*Approach 52 week low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low) stock price. *Approach 2 year high P/E* (*Approach 2 year low P/E*) is a dummy that equals 1 if P/E at day t-1 is within 5% below (above) the 2 year high (low). *Target price high 5%* is a dummy that equals 1 if stock price at day t-1 is within 5% below the target price issued by the same analyst who revises the recommendation. *Return* variables denote for cumulative return between days t or months m, where $Return_{t-5,\ t-1}$ is from day t-5 to t-1, $Return_{t-21,\ t-6}$ is from day t-21 to t-6, $Return_{m-6,\ m-2}$ is from month -6 to month -2, and $Return_{m-12,\ m-7}$ is from month -12 to month -7. *Forecast revisions* is rolling sum of previous six months' EPS revisions to price ratio. *SUE* is the standardized unexpected earnings. *Size* is the natural logarithm of market value at day t-22. *B/M* is book value of equity divided by market value of equity. *P/E* is price-to-earnings ratio based on actual earnings in the last available fiscal year. *Turnover* is average daily turnover in the previous three months divided by shares outstanding. *Accruals* are total accruals divided by average total assets on a quarterly basis. *Capex* is rolling sum of capital expenditure in the previous four quarters divided by average total assets. *Sales growth* is the rolling sum of sales in the previous four quarters divided by rolling sum of sales in the second preceding set of four quarters. *LTG* is median consensus long-term growth forecast. *Idiosyncratic volatility* is the standard deviation of the residuals of FF3-factor model. *Institutional ownership* is the ownership of institutes in percentages. *Analyst coverage* is number of analysts providing one-year earnings forecasts in prior three months. *Analyst dispersion* is the standard deviation across earnings forecasts in the prior three months. *Analyst experience* is the natural logarithm of recommendation revision year minus number of years plus one (or 0 if negative) since the analyst gave its first EPS estimate for the firm in question. Full definitions of control variables are found in Table 5. All regressions control for firm and year fixed effects. Coefficients are reported as log odds ratios and *z*-statistics are based on two-way clustered standard errors by firm and year. Sig. denotes for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

Probit model	(1)			(2)			(3)			(4)			(5)		
Downgrade	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat
Approach 52 week high	0.184	***	8.94	0.183	***	8.47	0.193	***	8.76	0.210	***	7.42	0.222	***	7.75
Approach 2 year high P/E	0.088	***	2.68	0.084	**	2.53	0.057	*	1.68	0.091	**	2.12	0.082	*	1.88
Target price high 5%	0.074	***	2.73	0.065	**	2.24	0.053	*	1.78	0.081	**	2.18	0.090	**	2.37
Approach 52 week low	0.199	***	5.96	0.219	***	6.36	0.199	***	5.68	0.218	***	4.81	0.212	***	4.65
Approach 2 year low P/E	-0.019		-0.48	0.010		0.24	0.052		1.28	0.110	**	2.08	0.119	**	2.26
$Return_{t-5,\ t-1}$				-0.077		-0.55	0.060		0.41	-0.031		-0.17	0.022		0.12
$Return_{t-21,\ t-6}$				1.096	***	11.83	1.193	***	12.23	1.285	***	10.70	1.323	***	11.01
$Return_{m-6,\ m-2}$				-0.247	***	-7.59	-0.142	***	-3.99	-0.070		-1.54	-0.056		-1.22
$Return_{m-12,\ m-7}$				-0.099	***	-3.44	-0.052	*	-1.68	-0.013		-0.32	-0.031		-0.75
Forecast revisions							-4.096	***	-8.36	-3.523	***	-5.41	-3.257	***	-5.00
SUE							0.011	**	2.39	0.001		0.13	-0.002		-0.32
Size										-0.007		-1.15	0.018	*	1.96
B/M										0.189	***	4.80	0.185	***	4.58
P/E										-0.001	**	-2.31	-0.001	**	-2.30
Turnover										0.004	***	3.12	0.001		0.66
Accruals										0.149		0.74	0.103		0.51
Capex										0.039		0.21	0.081		0.43
Sales growth										0.237	***	4.06	0.212	***	3.62
LTG										0.001		0.70	-0.001		-0.35
Idiosyncratic volatility													6.119	***	4.26
Institutional ownership													0.118	**	2.57
Analyst coverage													-0.319	**	-1.99
Analyst dispersion													-0.079		-1.41
Analyst experience													-0.003		-1.40
Analyst herding													0.171	***	4.05
Intercept	0.231	**	2.32	0.180	*	1.73	0.122		1.17	0.0391		0.12	-0.566	**	-2.29
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes		
Observations	35,270			30,015			28,572			17.713			17,537		
Wald chi^2	395.09			568.54			597.17			457.02			508.72		
Pseudo R^2	0.007			0.015			0.017			0.021			0.023		

Table 23. Subsamples with weekdays

This table shows subsample results with weekdays of conditional logit regression where dependent variable *Downgrade* is a dummy that equals 1 for recommendation downgrades and 0 for upgrades. *Approach 52 week high* (*Approach 52 week low*) is a dummy that equals 1 if stock price at day t-1 is within 5% below (above) the 52-week high (low). *Approach 2 year high P/E* (*Approach 2 year low P/E*) is a dummy that equals 1 if P/E at day t-1 is within 5% below (above) the 2 year high (low). *Target price high 5%* is a dummy that equals 1 if stock price at day t-1 is within 5% below the target price issued by the same analyst who revises the recommendation. *Return* variables denote for cumulative return between days t or months m, where $Return_{t-5,\ t-1}$ is from day t-5 to t-1, $Return_{t-21,\ t-6}$ is from day t-21 to t-6, $Return_{m-6,\ m-2}$ is from month -6 to month -2, and $Return_{m-12,\ m-7}$ is from month -12 to month -7. *Forecast revisions* is rolling sum of previous six months' EPS revisions to price ratio. *SUE* is the standardized unexpected earnings. *Size* is the natural logarithm of market value at day t-22. *B/M* is book value of equity divided by market value of equity. *P/E* is price-to-earnings ratio based on actual earnings in the last available fiscal year. *Turnover* is average daily turnover in the previous three months divided by shares outstanding. *Accruals* are total accruals divided by average total assets on a quarterly basis. *Capex* is rolling sum of capital expenditure in the previous four quarters divided by average total assets. *Sales growth* is the rolling sum of sales in the previous four quarters divided by rolling sum of sales in the second preceding set of four quarters. *LTG* is median consensus long-term growth forecast. *Idiosyncratic volatility* is the standard deviation of the residuals of FF3-factor model. *Institutional ownership* is the ownership of institutes in percentages. *Analyst coverage* is number of analysts providing one-year earnings forecasts in prior three months. *Analyst dispersion* is the standard deviation across earnings forecasts in the prior three months. *Analyst experience* is the natural logarithm of recommendation revision year minus number of years plus one (or 0 if negative) since the analyst gave its first EPS estimate for the firm in question. All regressions control for year and SIC 10 industry fixed effects. Coefficients are reported as log odds ratios and *z*-statistics are based on two-way clustered standard errors by firm and year. Sig. denotes for significance and ***, **, and * denote the statistical significance levels at the 1%, 5% and 10%, respectively.

Cond. logit model	Monday			Tuesday			Wednesday			Thursday			Friday		
Downgrade	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat	Coef.	Sig.	*z*-stat
Approach 52 week high	0.318	***	2.63	0.426	***	4.02	0.345	***	2.87	0.392	***	3.38	0.287	**	2.40
Approach 2 year high P/E	0.145		0.90	0.028		0.15	0.200		1.22	0.138		0.62	0.098		0.56
Target price high 5%	0.102		0.59	0.357	*	1.80	0.167		0.79	0.038		0.22	0.086		0.53
Approach 52 week low	0.334	*	1.82	0.340	*	1.86	0.352	**	2.21	0.230		1.36	0.441	**	1.98
Approach 2 year low P/E	0.182		0.65	0.026		0.12	0.280		1.36	0.207		0.90	-0.028		-0.11
$Return_{t-5,\ t-1}$	0.062		0.05	0.596		0.52	0.756		0.49	-0.931		-0.89	-0.479		-0.35
$Return_{t-21,\ t-6}$	2.438	*	1.87	1.984		1.33	1.731	*	1.76	2.536	*	2.01	2.425		1.60
$Return_{m-6,\ m-2}$	0.104		0.31	-0.402	*	-1.75	-0.052		-0.26	-0.067		-0.22	-0.032		-0.11
$Return_{m-12,\ m-7}$	0.033		0.13	-0.065		-0.29	0.107		0.41	-0.148		-0.60	-0.185		-0.63
Forecast revisions	-9.159	***	-3.46	-0.574		-0.22	-6.089	**	-2.01	-4.304		-1.39	-2.871		-0.91
SUE	-0.042		-0.99	-0.058	*	-1.93	0.006		0.11	0.055		1.56	0.006		0.14
Size	0.099		0.11	0.044		0.05	-0.010		-0.01	0.030		0.03	0.021		0.02
B/M	0.349		0.26	0.199		0.13	0.170		0.12	0.383		0.22	0.539		0.28
P/E	-0.001		-0.72	0.000		0.13	-0.001		-0.33	-0.003		-0.99	-0.001		-0.24
Turnover	0.002		0.34	-0.012		-1.26	-0.002		-0.19	0.013		1.57	0.011		1.73
Accruals	0.331		0.28	1.142		0.97	-1.008		-1.35	1.005		0.95	0.466		0.42
Capex	0.538		0.18	-1.106		-0.40	-0.146		-0.05	1.577		0.55	-0.860		-0.30
Sales growth	0.605		0.46	0.245		0.24	0.211		0.18	-0.001		0.00	0.460		0.38
LTG	-0.001		-0.07	-0.002		-0.08	-0.007		-0.28	0.005		0.20	0.007		0.22
Idiosyncratic volatility	7.636		0.21	21.027		0.45	7.389		0.18	5.661		0.14	5.102		0.12
Institutional ownership	0.323		0.30	0.391		0.30	0.047		0.05	0.022		0.02	-0.039		-0.04
Analyst coverage	-1.756		-0.19	-0.788		-0.08	-0.462		-0.05	-0.451		-0.05	0.322		0.03
Analyst dispersion	-0.497		-0.60	0.171		0.19	0.063		0.06	-0.041		-0.05	-0.425		-0.42
Analyst experience	-0.013		-0.79	-0.003		-0.36	0.010		0.83	-0.004		-0.29	-0.008		-0.70
Analyst herding	-0.018		-0.09	0.129		0.40	0.440	*	1.70	0.263		1.64	0.420	**	2.40
Year fixed effects	Yes			Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes			Yes		
Observations	3,638			3,380			3,642			3,682			3,004		
Wald chi^2	94.36			98.90			74.92			96.49			74.95		
Pseudo R^2	0.027			0.027			0.020			0.026			0.028		

6. Conclusion

This thesis studies the functions of historical stock price and valuation anchors on analyst recommendation revisions. The anchors I have analyzed include the most commonly used relative valuation multiples and 52-week high and low stock prices. A specific focus is on the relative valuation multiples, particularly in forward-looking P/E ratio since analysts often justify their recommendations with P/E ratio (Bradshaw, 2002). The sample consists of 35,270 analyst recommendation revisions from 5,193 analysts for 1,454 unique US stock-listed companies during the period of November 1993 to September 2015.

A key finding is that analysts partly anchor their views on the company by using both the 52-week high and low stock prices as reference points to revise their recommendations. The odds of being downgraded by analysts are 44.8% higher for companies approaching the 52-week high stock price and 43.6% higher for companies approaching the 52-week low stock price[16]. The effect is stronger with the 52-week high stock price and also robustness checks support the findings. Furthermore, results suggest that analysts may also somewhat anchor to their own target prices when revising their recommendations. However, the target price findings are only statistically significant at the 10% level.

The findings on the 52-week high and low are partially consistent with prior literature. Li et al. (2016) find similar reaction with the 52-week high stock price but they do not find statistical significance for the 52-week low reference point. However, academic literature is mixed on the effect of the 52-week low as there are also many papers suggesting that 52-week low is an important anchor for investors and e.g. George and Hwang (2004) find negative abnormal returns for stocks trading close to their 52-week low. Furthermore, one could argue that if the 52-week low stock price is important anchor for investors, it is also important for analysts because analysts' beliefs are seen as a good proxy for the beliefs held by investors in general (Bradshaw, 2011).

My thesis also provides new insight on anchoring to valuation multiples. To my best knowledge, the effects of relative valuation multiples on analyst recommendation revisions have not been studied before. My results show that analysts tend to downgrade stock recommendations when median forward-looking P/E ratio is approaching the 2-year high and 2-year low P/E ratio. Nevertheless, results of the anchoring effect on P/E ratios are statistically significant merely at the 10% level when the anchoring effects of the 52-week high and low stock price as well as

[16] Including all control variables (results from Table 8 and Table 9).

analysts' own target price are also controlled in the regressions. Then, the odds of being downgraded by analysts are 14.8% and 19.6% higher for companies when the P/E ratio is approaching the 2-year high and 2-year low P/E, respectively. The magnitude is substantial but over two times smaller compared to the 52-week high and low phenomena where the odds of being downgraded are over 40% higher for companies approaching either the 52-week high or low than that for other companies[17]. In addition, another interesting finding is that when the P/E and stock price are approaching the 2-year low P/E and 52-week low stock price at the same time, the effect on downgrade is strongly inverse and thus the analyst is more likely to upgrade the recommendation in these reference points. One potential explanation is an underreaction to company-specific negative earnings news and that the stock has hit a 'support level' in the analyst's mind meaning that the analyst thinks that stock price cannot continue to drop further.

When it comes to other commonly used valuation multiples and alternative measures, it seems that even though there is a positive correlation between the high (low) P/E approach dummies to the high (low) approach dummies based on other valuation multiples, anchoring effects are most strongly present by using the median forward-looking P/E multiples. Only approaching the 2-year low PEG dummy shows statistical significance from the forward-looking valuation multiples tested when all controls are included. Nevertheless, this is fully in line with the findings of Bradshaw (2002) who finds that on top of P/E ratio, analysts also use PEG ratio to justify their recommendations.

However, the effect of anchoring on the P/E ratio loses statistical significance in a robustness check where regressions are run separately for each weekday. The same holds true for the two most important control variables that are actually the most powerful variables and have the greatest effect on downgrades. These control variables yield statistically significant results at the 1% level in all the main tests. A stock's recent price momentum in the previous weeks (cumulative return between trading days t-21 and t-6 before the recommendation revision day t) seem to increase the odds of downgrading substantially whereas an increase in the sum of prior six months' earnings forecast revisions (scaled by price) seem to decrease the odds of downgrading substantially.

This thesis offers numerous possibilities for further research in analyzing the analysts' decision-making process. Even though the literature on analysts is vast, there is only a limited number of studies analyzing the behavioral side of analysts regarding how analysts actually process

[17] Results from Table 16 with all control variables.

information and draw conclusions. The main avenue for further research would be studying more on the anchoring effects based on the rule-of-thumb valuation heuristics. For instance, this thesis focuses on the effect of P/E ratios derived from consensus earnings estimates. Another potential measure is using the analyst's own earnings estimates. There is mixed evidence on how analysts incorporate their own earnings estimates into their recommendations but this would be an interesting new avenue for further studies. Furthermore, one topic for further studies would be investigating whether analysts anchor their recommendation revisions to the industry level valuation ratios. However, each analyst may perceive a company's peer/industry group differently and thus researchers should be open for alternative methods of measuring these anchoring effects. It would also be interesting to examine what effect the analyst's industry knowledge plays in the decision making – how the decision making process differs between analysts focusing on one industry and analysts focusing on multiple industries. Are analysts focusing on multiple industries more prone to use rule-of-thumb heuristics to revise their recommendations?

To conclude, reference points based on historical stock prices such as 52-week high and low stock prices seem to drive the results more than valuation based reference points. The results support the conclusion that the anchoring phenomenon weakens when P/E and PEG multiples are used and results weaken even further when other market multiples are used. Analysts partly anchor their recommendation revisions to 52-week high and low stock prices, resulting in an increased downgrade probability near these price points. Thus, analysts are more likely to make better recommendation decisions if they acknowledge the possibility that they are anchoring their revisions to these reference points that may have no informational value. Investors may also be better off if they avoid making investment decisions based on analyst downgrades when stock prices are approaching the 52-week high and low.

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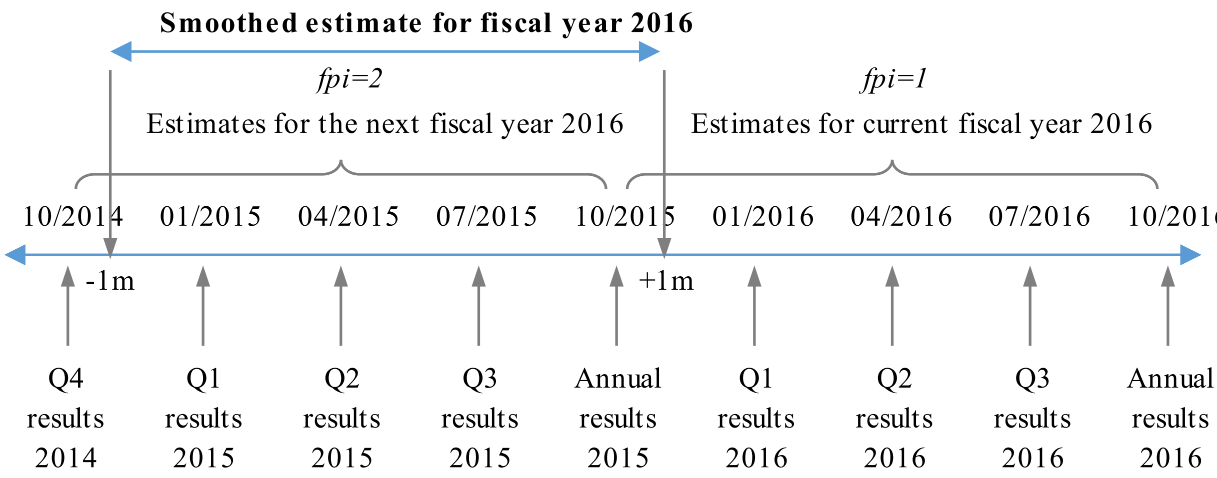
Appendix

Figure 6. Illustration of forecast horizon for Apple Inc.



This figure illustrates how forward-looking earnings estimates are used in this thesis. Apple Inc. is used as an example[18] and Apple's quarterly and annual earnings announcement months between the end of 2014 and 2016 are illustrated. Calculating daily P/E multiples for 2016 using earnings estimates from the same fiscal year 2016 (fpi=1) may be misleading as accuracy changes significantly during the year and estimates are only slightly forward-looking when the end of the period comes closer. Thus, when new quarterly earnings are announced, estimation accuracy for the fiscal year increases. However, accuracy remains relatively stable for estimates for the next fiscal year (fpi=2) as there is at least 12 months to wait until the announcement of the annual results. Apple Inc's estimates for the next fiscal period 2016 (fpi=2) are given from 10/2014 until 10/2015. Accuracy remains relatively similar between the beginning and in the end of that forecast period as they are more forward-looking compared to current fiscal year estimates (fpi=1).

Nevertheless, I consider it important to smooth the next fiscal year estimates (fpi=2) by using the first two months of the current fiscal year estimates (fpi=1) in order to diminish the time period jump after the publishing of annual results. By then, an analyst has had enough time to revise their recommendations (1-2 months). Analysts often revise their recommendations after earnings announcements (Yezegel, 2015) and if I only use estimates for the next fiscal year (fpi=2), the estimation window after the announcement of annual results would jump from ~12 months to ~24 months. In the example, there are 12 months until the end of the next fiscal period in October 2015 but in November 2015, there are 24 months until the end of the next fiscal year period (as the period changes). If the period is not smoothed, there could be many high and low points of P/E after the annual results have become public that are actually due to the change in earnings estimation window, biasing the results.

[18] See Apple's earnings announcement dates from the website http://investor.apple.com/financials.cfm (accessed 21.12.2016).